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AUTHOR Thompson, Bruce
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ABSTRACT

This paper provides an introduction to basic issues concerning structural equation modeling (SEM), a research methodology increasingly being used in social science research. First, seven key issues that must be considered in any SEM analysis are explained. These include matrix of associations to analyze, model identification, parameter estimation theory, multivariate normality, model misspecification and specification searches, sample size, and measurement model adequacy. Second, heuristic SEM analyses involving structural models are presented to demonstrate how SEM takes score measurement reliability into account and how SEM may shed light on causal issues. Finally, ten commandments for proper SEM use are presented, among which are the following: (1) never conclude that a model has been definitely proven; (2) for specification searches that require larger samples, test the re-specified model with a "hold-out" or independent sample and never change a specification without a theoretical justification; (3) test multiple plausible rival models; and (4) don't use SEM with small samples. Appendices provide five examples of statistical analyses using SEM. (Contains 66 references.) (DB)

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The Ten Commandments of Good Structural Equation Modeling Behavior: A User-friendly, Introductory Primer on SEM

Bruce Thompson

Texas A&M University 77843-4225
and
Baylor College of Medicine

B. THOMPSON

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Abstract

The present paper provides a user-friendly introduction to and guidance regarding some of the basic issues that must be resolved to conduct structural equation modeling (SEM). The paper incorporates many of the latest findings regarding covariance structure analysis, and presumes no SEM background on the part of the reader. First, *seven key issues* that must be considered in any SEM analysis are explained. Second, *heuristic SEM analyses* involving structural models are presented to make clear in a concrete fashion (a) how SEM takes score measurement reliability into account and (b) how SEM may shed some limited light on causal issues. Third, *10 commandments* for proper SEM behavior are presented.

Structural equation modeling (SEM; also variously called covariance structure analysis and, somewhat speciously, causal modeling) is being increasingly used within the social science literature. Indeed, it would be difficult to locate recent issues of social science journals in which some SEM applications were not reported. And one new journal--Structural Equation Modeling: A Multidisciplinary Journal--has been created that is exclusively devoted to SEM reports and issues. SEM has been termed "the single most important contribution of statistics to the social and behavioral sciences during the past twenty years" (Lomax, 1989, p. 171). Similarly, Stevens (1996) argued that SEM techniques "have been touted as one of the most important advances in quantitative methodology in many years" (p. 415). Many would regard this as an understatement, though it is also clear that SEM is sometimes used when much simpler methods would suffice.

It is also clear that SEM is sometimes not correctly used. Of course, some misuses and errors are to be expected with a method that is relatively new, that is still undergoing refinement at a seemingly exponential rate, and that many social scientists are still learning.

SEM has historical roots in two major classical traditions. First, SEM always invokes a ***"measurement model"*** specifying that the *measured/observed* variables reflect underlying *latent/synthetic* variables, and sometimes is even used exclusively to investigate measurement issues (i.e., "confirmatory factor analysis"); this aspect of structural modeling dates back to factor analysis theory

articulated by Spearman (1904). Second, sometimes a regression structure among the latent/synthetic variables defined by the measurement model(s), called a ***"structural model"***, is also specified and tested; this aspect of SEM can be traced back to path analysis methods (cf. Wright, 1921, 1934).

However, the modern roots of SEM can be traced especially to the theoretical developments formulated by Karl Jöreskog (cf. 1967, 1969, 1970, 1971, 1978), and to the computer program, LISREL (i.e., analysis of LInear Structural RELationships) developed by Jöreskog and his colleagues (e.g., Jöreskog & Sörbom, 1989). Today, modern SEM software is extremely user-friendly, and allows users of microcomputers to declare models to be tested using software-aided drawings and point-and-click menus. Particularly respected today for both their technical accuracy and their user-friendliness are the two microcomputer software packages, EQS (Bentler, 1992a) and AMOS (Arbuckle, 1997).

Accessible short treatments of SEM have been provided by Baldwin (1989), Mueller (1997), and Lomax (1989). Extraordinarily good longer treatments, which include numerous examples and focus on EQS and LISREL, are the various works by Barbara Byrne (cf. 1994, 1998; also see Long (1983a, 1983b)).

The purpose of the present paper is to provide a user-friendly introduction to and guidance regarding some of the basic issues that must be resolved to conduct structural equation modeling. First, *seven key issues* that must be considered in any SEM analysis are explained. Second, *heuristic SEM analyses* involving structural

models are presented to make clear in a concrete fashion (a) how SEM takes score measurement reliability into account and (b) how SEM may shed some limited light on causal issues. Third, *10 commandments* for proper SEM behavior are proffered.

Seven Key Decisions in SEM Analysis

1. Matrix of Associations to Analyze

Most researchers today (hopefully) realize that all parametric statistical analyses are special cases within a single general linear model (GLM) family. In one of his innumerable seminal contributions, the late Jacob "Jack" Cohen (1968) demonstrated that multiple regression subsumes all the univariate parametric methods (e.g., t-test, ANOVA, ANCOVA) as special cases. Subsequently, Knapp (1978) presented mathematical theory showing that canonical correlation analysis subsumes all the parametric analyses, both univariate and multivariate, as special cases. Fan (1996a) and Thompson (1984, 1991) present concrete demonstrations of these relationships.

However, structural equation modeling (SEM) is an even bigger conceptual tent subsuming narrower special cases (Bagozzi, Fornell & Larcker, 1981), including both canonical correlation analysis and multiple regression. Illustrations of these relationships have been offered by Fan (1997) and by Thompson (1998a).

The general linear model is a powerful heuristic device that can help researchers see three important commonalities that exist across various analytic methods. First, all these methods use weights (e.g., regression beta weights, standardized canonical

function coefficients) to optimize explained variance and minimize model error variance. Second, all the methods focus on the latent synthetic variables (e.g., the regression $\hat{Y}$ variable, factor scores) created by applying the weights (e.g., beta weights) to scores on measured/observed variables (e.g., regression predictor variables); we take these latent/synthetic variables as measures of our constructs. Third, all analytic methods are correlational (Knapp, 1978; Thompson, 1998a) and yield variance-accounted-for effect sizes analogous to r^2 (e.g., R^2, η^2, ω^2).

The commonality that all parametric methods apply weights to the measured/observed variables to compute latent/synthetic variables is obscured by the inherently confusing language of traditional statistics. As I have noted elsewhere, the weights in different analyses

> ...are all analogous, but are given different names in different analyses (e.g., beta weights in regression, pattern coefficients in factor analysis, discriminant function coefficients in discriminant analysis, and canonical function coefficients in canonical correlation analysis), mainly to obfuscate the commonalities of [all] parametric methods, and to confuse graduate students. (Thompson, 1992, pp. 906-907)

Indeed, both the weight systems (e.g., regression equation, factor, canonical function) and the synthetic variables (e.g., the regression $\hat{Y}$ variable, factor scores, discriminant function scores)

are also arbitrarily given different names across the analyses, again mainly so as to confuse the graduate students.

The first step of GLM analyses often involves the computation of a matrix of associations (e.g., Pearson product-moment correlation matrix, variance/covariance matrix) among the measured/observed variables. In fact, with only this matrix (as will be seen momentarily) many GLM analyses can be replicated.

SEM analyses can be based on numerous matrices of association (e.g., product-moment correlation, polychoric correlation). Some researchers prefer to analyze Pearson correlation coefficients. These association coefficients are "scale-free," because the standard deviations of a given pair of variables have been removed from the covariance of the two variables by division (i.e., $r_{XY} = COV_{XY} / [SD_X * SD_Y]$). Thus, the weights derived from these correlations are themselves "scale-free," and can be more readily interpreted in relation to each other because all the measured variables have been effectively "standardized" by this process.

However, most SEM theory was developed for application with the matrix of associations among the measured/observed variables being a variance/covariance matrix (i.e., variances on the diagonal, covariances off the diagonal). And it has been established that while using the product-moment correlation matrix may be appropriate with some models, for other models some SEM statistics will be incorrect unless the variance/covariance matrix is employed (Cudeck, 1989).

It is also very important that the level of scale of the

measured variables (e.g., categorical/nominal, ordinal/ranked, continuous/interval) is honored when selecting a given matrix of associations to be computed and analyzed. Of course, to some degree judgments about measurement scale are subjective, and researchers may reasonably disagree regarding some of these decisions. However, data might be analyzed using a variety of plausible matrices of association, to confirm that results are not artifacts of methods choices.

2. Model Identification

When we conduct analyses, we are fitting a model to our data and estimating the weights and other parameters (e.g., latent variable variances and/or covariances) associated with that model. A critically important issue in this process involves determining whether the model is ***"identified"***. A model is identified if, given the model and the data, a single set of weights and other model parameters can be computed. If infinitely many sets of weights and other parameters are plausible, the parameters are mathematically indeterminate, and the model is not identified (i.e., "under-identified"). As Byrne (1998) noted, "statistical identification is a complex topic that is difficult to explain in nontechnical terms" (p. 28; see Mueller (1997, pp. 358-359) for a fairly accessible summary of the conditions sufficient for model identification).

One key issue as regards identification involves degrees of freedom. The notion of identification can be partially explored in the context of classical statistics (e.g., product-moment correlation, multiple regression). The degrees of freedom total in

classical univariate analyses equals n-1. If we have scores of only two people on only two variables, the model degrees of freedom is 1 and the degrees of freedom error is 0; here, no matter what the scores on the two variables, the r^2 value can only be 1.0. This result can be computed, although the computation is a waste of time, because only one result is plausible when a model is "just-identified". Similarly, scores of three people on one criterion variable and two predictor variables would yield a degrees of freedom error of 0, and an inescapable R^2 value of 1.0.

In SEM degrees of freedom total is a function of the number of nonredundant pieces of information present in the matrix of associations being analyzed (and not of the number of people). For example, with eight measured variables, there would be eight variances and 28 nonredundant (either below or above the diagonal) covariances ([8 * (8-1)] / 2 = [8 * 7] / 2 = 56 / 2 = 28). This would result in 36 (8 + 28 = 36 = [8 * (8+1)] / 2 = 72 / 2) degrees of freedom being available for any SEM model being fit to these data.

In SEM each parameter (e.g., weight, path coefficient, variance of or covariance among latent/synthetic variables) that we estimate takes one degree of freedom. Thus, for the problem involving eight measured variables, if we specify a model involving the estimation of 36 model parameters, the model will be just-identified. These parameters can be estimated (i.e., the parameters are mathematically determined, with only one plausible set of estimates). However, the results from a just-identified SEM model

are just as interesting as were the results from an r^2 analysis involving scores of two people on two measured/observed variables (i.e., interest in the results for a model with zero degrees of freedom equals that degrees of freedom), because such models will always exactly reproduce the analyzed matrix of associations.

We are scientifically most interested in SEM models that spend fewer degrees of freedom (i.e., estimate fewer model parameters), and are thus more parsimonicus. When models have more degrees of freedom (i.e., there are a lot more degrees of freedom total than the number of estimated parameters), but still do reasonably well at reproducing the matrix of associations, there are more ways in which the models are potentially falsifiable, and so such models represent more rigorous and persuasive tests of our conceptions of latent constructs (Mulaik, 1987, 1988; Mulaik, James, van Alstine, Bennett, Lind & Stilwell, 1989). In other words, we prefer models that are considerably "over-identified."

Having more than zero degrees of freedom is a necessary-but-not-sufficient condition for model identification. That is, we simply cannot estimate the parameters for any "under-identified" model.

SEM computer programs tend to run diagnostics that indicate when models have not been identified. When this occurs, some parameters for which estimates were initially requested (i.e., "freed" to be estimated) must be "fixed" as not being estimated (e.g., a weight or the latent/synthetic variable's variance is "fixed" to equal 1.0, or the error variance of a measured/observed

variable is "fixed" to equal .0).

3. Parameter Estimation Theory

Classical univariate and multivariate parametric analyses (e.g., t-tests, ANOVA, descriptive discriminant analysis) invoke a statistical theory of parameter estimation called ***"ordinary least squares"***. There are, in fact, numerous other statistical theories that can be invoked to estimate freed model parameters. Among these various alternatives are ***"maximum likelihood"*** (ML), ***"generalized least squares"*** (GLS), and ***"asymptotically distribution-free"*** (ADF; Browne, 1984) estimation theories. The various estimation theories differ as regards both their assumptions and their theoretical properties.

For example, as regards assumptions both maximum likelihood and generalized least squares estimations presume that the data have a multivariate normal distribution. Of course, this distributional assumption also invokes issues involving the measurement scale of the measured/observed variables, because, for example, dichotomous variables cannot be even univariate normally distributed, even if the dichotomous variable scores are symmetrical. ADF estimation, on the other, does not require the assumption of multivariate normal distribution. West, Finch and Curran (1995) review some relevant issues and choices regarding distributional assumptions.

In most SEM computer programs ML estimation is the default. Perhaps for this reason maximum likelihood estimation is used with considerable frequency. ML estimates seek to estimate parameters

that best reproduce the estimated *population* variance/covariance matrix. Of course, this may be another reason for the frequent use of this estimation method, since accurate estimates of population parameters in theory should result in result replicability.

4. Multivariate Normality

A necessary but not sufficient condition for multivariate normality is bivariate normality of all pairwise combinations of the measured/observed variables. In turn, a necessary but not sufficient condition for bivariate normality is univariate normality of all the measured/observed variables.

However, even just univariate normality is a more elusive concept than most researchers realize (Bump, 1991). There are infinitely many univariate normal data distributions, each differing in appearance. [Some researchers have been lulled into the misconception that all univariate normal distributions have a single classic "bell shape," because almost all textbooks only present graphs of the normal distributions of z-scores. However, for data not in z-score form, there are infinitely many plausible symmetrical distributions that are normal, but that differ markedly in appearance.]

There is no definitely superior method by which to establish that the multivariate normal distribution assumption has been met, so that certain estimation theories can then be employed. Ashcraft (1998) reviews some of the available choices.

One user-friendly method for evaluating multivariate normality invokes a graphical procedure. Thompson (1990) describes this

method in more detail. Appendix A presents an SPSS for Windows version of this program. Fan (1996b) has made available a SAS version of this program.

5. Model Misspecification and Specification Searches

All over-identified models portray the relationships among measured and latent variables. The goal is to specify these relationships for the population, so that future samples from the same population will yield comparable findings. The model is over-identified partly so that the model is falsifiable, but also because we seek simplifications of reality that remain useful but make our understandings of reality more manageable. As Mueller (1997) noted,

> A structural equation model is nothing more than an oversimplified approximation of reality, no matter how carefully conceptualized. A good model can be characterized as featuring an appropriate balance between efforts to represent a complex phenomenon in the simplest [most parsimonious] way and to retain enough complexity that [still] leads to the most meaningful [and true] interpretations possible. (p. 365)

A perfectly "specified" over-identified model would perfectly reproduce the associations among the measured/observed variables. However, because the model is over-identified, the model will never perfectly reproduce data in either the sample or the population. Thus, we must somehow evaluate whether the model is sufficiently

adequate to remain both reasonably manageable and reasonably correct.

Model Misspecification. If the model is deemed to not be correct, the model is deemed ***"mispecified"***. Making this judgment is critical, because the SEM parameter (e.g., weights, variances, covariances) estimation processes

> all fail to provide correct sample estimates, standard errors, and data-model fit chi-square statistics... if the model under consideration is misspecified and does not reflect at least a very close approximation to the true structure in the population. (Mueller, 1997, p. 359)

Of course, since a simplified model of reality is always at least partially misspecified, making the judgment as to when a model is misspecified can be challenging.

Through the years myriad fit statistics have been developed to aid in making these judgments. Byrne (1998, pp. 109-119) reviews some of the fit statistics provided by the SEM computer programs. Arbuckle (1997, pp. 551-572) summarizes some of the relevant formulae used to compute these statistics, and summarizes a bit of the literature on rules of thumb for interpreting these values.

However, the stark, harsh reality is that we still have much to learn regarding both how these SEM fit statistics operate under different conditions and what should be the cutoffs for declaring reasonable model fit. Indeed, until recently too much of the Monte Carlo simulation work on these issues failed to use misspecified

models, meaning that the results did not directly bear upon the real-world situation in which the model is at least partially misspecified and the researcher does not know for certain which or how many features of the model specification are correct (Fan, Thompson & Wang, in press; Fan, Wang & Thompson, 1997).

A very important consideration in evaluating the fit of a given model involves the modeling context of this judgment. The most persuasive case that a model has been correctly specified is created when a researcher finds differentially better fit of a given model against the fit of numerous other defensible, thoughtfully-formulated, rival plausible models. Thus, multiple models should usually be evaluated in any SEM project.

It is also critical to remember that even such findings do not conclusively establish that a single given model is definitively correct. Infinitely many models can fit a given data set. Thus, the fit of a single tested model is always an artifact of having not tested all possible models.

In any case, also remember that we are defining an over-identified model to simplify reality. We seek a simplification that we subjectively judge to be inherently somewhat inaccurate but still reasonably useful and more manageable. We are not seeking a single truth in the context of a simplification that inherently distorts some features of reality. We use model fit statistics to assist us in making these judgments, but the judgment we make is inherently subjective. We then must accept the responsibility for the construct definitions we formulate (Mulaik, 1994).

Model Fit Statistics. Given space limitations, only a few of the myriad model fit statistics can be reviewed here (Bentler, 1994). A χ^2 *goodness-of-fit test statistic* can be computed to test the null hypothesis that the variance/covariance matrix reproduced by the freed model parameter estimates equals the variance/covariance matrix (i.e., that the model exactly reproduces all observed relationships). This statistic is printed by all the SEM computer programs. Note that here, as against in traditional statistical significance testing, the researcher hopes to not reject this null hypothesis, so that the model can be taken as fitting the data.

Even though this application of statistical testing is a variant on usual practice, one of the numerous criticisms of classical statistical significance testing applies here also: the result is partially an artifact of sample size (cf. Cohen, 1994; Thompson, 1996, 1998b, in press-a, in press-b, in press-c). As Bentler and Bonett (1980) made very clear,

> [I]n very large samples virtually all models that one might consider would have to be rejected as statistically untenable... This procedure cannot be justified, since the chi-square variate y can be made small by simply reducing sample size. (p. 591)

However, the chi-square statistic can be of some use in comparing the fits of models for a given data set with a single sample size, particularly if the models are "nested" within each other (cf. Jöreskog & Sörbom, 1989, pp. 230-233).

The *Goodness-of-Fit Index* (GFI) and the ***Adjusted Goodness-of-Fit Index*** (AGFI) (Jöreskog & Sörbom, 1984) essentially compare the ability of a model to reproduce the variance/covariance matrix to the ability of no model at all to do so. The AGFI adjusts the GFI for the number of degrees of freedom expended in estimating the model parameters. Indices less than zero are treated as zero, and range up to one, with one indicating perfect model fit. Most researchers expect these values to be greater than .9 or .95 for correctly specified models.

The ***Root Mean-square Residual*** (RMR) evaluates the average residual value for the variance/covariance matrix reproduced by the model parameters and the actual variance/covariance matrix. The RMR can range down to zero, which would indicate perfect model fit. A well-fitting model will have values of "say, .05 or less" (Byrne, 1998, p. 115).

Bentler and Bonett (1980) proposed a ***Normed Fit Index*** (NFI), which compares model fit to that of a model for the same data presuming independence of the measured/observed variables. NFI ranges between zero and one, with higher values indicating better fit. Usually values greater than .9 or .95 are considered as reflecting adequate fit.

The Bentler and Bonett article has been one of the most widely cited articles in the psychological literature (see Bentler (1992b)). However, NFI has been shown to be an underestimate when small samples are used. Consequently, Bentler (1990) proposed an adjustment to the NFI, the ***Comparative Fit Index*** (CFI), which takes

sample size into account. Some have suggested that the CFI should be a fit statistic of choice in SEM research (Byrne, 1998).

Various ***parsimony-weighted fit indices*** have been proposed (see Mulaik et al. (1989), but also Marsh and Hu (1998)). These fit statistic weights, which range up to one and down to zero for just-identified models, are multiplied times indices such as the NFI, to take model complexity into account and reward models that estimate fewer parameters.

Some fit indices focus on estimated population fit. Steiger and Lind (1980) proposed a ***Root Mean Square Error of Approximation*** (RMSEA). As Byrne (1998) noted, RMSEA "has only recently been recognized as one of the most informative criteria in covariance structure modeling" (p. 112). Values approaching zero are desired, and "a value of .08 or less for RMSEA would indicate a reasonable error of approximation" (Browne & Cudeck, 1993).

The various fit indices provide a constellation of information about the competing models being considered in an SEM analysis. Because some of the different fit indices evaluate different aspects of fit, it is important to evaluate fit based on multiple fit statistics, so that judgments will not be an artifact of analytic choice. Furthermore, as Byrne (1998) so correctly emphasized, "[A]ssessment of model adequacy must be based on multiple criteria that take into account theoretical, statistical, and practical considerations" (p. 119).

Specification Search. In addition to providing fit indices for a given model, SEM analyses also provide important information

regarding exactly where potential model specification errors may have occurred. There are two possible types of errors, and different information is used to evaluate each of the possibilities.

First, model misspecification may involve having "freed" a parameter to be estimated when, if fact, the parameter is not very useful in reproducing relationships, and should instead have been "fixed" (e.g., two latent/synthetic variables should have been constrained to be uncorrelated in the model, or the measurement error variance of a measured/observed variable should have been constrained to be zero). In classical statistics, the ratio of a mean to the standard error of the mean can be computed, and is called the calculated test statistic, t. For most sample sizes, a $t_{CALCULATED}$ greater than two in absolute value is statistically significant at approximately the α=.05 level.

In SEM ***t statistics*** (sometimes also called Wold statistics) can be computed by dividing any given parameter estimate by its standard error. Any ratio less than $|2|$ suggests a possible model specification error in the form of "freeing" a parameter than instead might have been "fixed."

Second, model misspecification may involve having "fixed" a parameter to not be estimated when, if fact, the parameter might be very useful in reproducing relationships, and should instead have been "freed." SEM computer programs upon request will provide ***modification indices*** for each "fixed" model parameter; these modification indices indicate approximately how much smaller (i.e.,

better) the model chi-square statistic would get if a given "fixed" parameter was instead "freed." Large values for these indices may indicate that freeing a given fixed parameter should be considered.

The process of modifying an *a priori* model based on such results is called a ***specification search***. This practice is considerably controversial (see Mueller (1997)), unless the model is changed based on statistical results for one sample, and then the re-specified model is evaluated in an independent sample. Clearly, the more model features that are altered based on sample results, the greater is the likelihood that sampling error variance (i.e., the variability reflecting the idiosyncratic and non-replicable features of a given sample) is being capitalized on, leading then to non-replicable model fit.

Furthermore, model specification should never be based on blind dust-bowl empiricism. Models should only be re-specified in those cases where the researcher can articulate a persuasive rationale as to why the modification is theoretically and practically defensible.

6. Sample Size

Structural equation modeling is inherently a **large-sample** technique. At least four cases in which especially even larger samples are needed can be noted. First, even larger samples are needed as more measured/observed variables are employed. Second, even larger samples are required as more complex models are evaluated. Third, even larger samples are needed when more elegant parameter estimation theories (e.g., asymptotically distribution-

free estimation) are employed. Fourth, even larger samples are needed if the researcher is going to do any model search specification.

Some have suggested that sample size should be at least 200 (Baldwin, 1989). Similarly, Lomax (1989) suggested "a sample size of at least 100 (if not 200)" (p. 189). Furthermore, it has been suggested that the ratio of the number of people to the number of measured/observed variables should be at least 10:1 (Mueller, 1998), if not 15:1 or 20:1. Thus, in even the most straightforward SEM applications, sample size should probably be the minimum of (a) 100 to 200 people, or (b) an n:v ratio of at least 10:1 or 15:1. MacCallum, Browne and Sugawara (1996) have provided some statistical methods for more precisely estimating the sample size necessary for a given SEM problem.

7. Measurement Model Adequacy

As noted previously, SEM structural models incorporate several measurement models in which measured/observed variables are taken as reflecting underlying latent constructs in the form of latent/synthetic variables, and the regression path models of some of these latent/synthetic variables with each other are then estimated. Researchers have increasingly recognized that the measurement models within SEM structural models have often been the weak links in past SEM analyses.

Put simply, if the specified measurement models do not fit the measured variables, then knowing the relationships among the latent/synthetic variables defined by these measurement models is

essentially useless. Thus, some researchers (cf. Anderson & Gerbing, 1988) have recommended that SEM structural analyses should be approached as a two-step hierarchical process: first confirm that the specified measurement models all fit their respective data, and only then explore the structural relationships among the latent/synthetic variables.

It has been generally agreed that it is useful to explore the measurement models embedded within structural models prior to evaluating the structural models. However, some have argued that measurement models may also be reasonably re-evaluated and perhaps respecified within the subsequent structural model analyses (see Hayduk, 1996).

But it is quite clear that bad measurement models make the related structural models uninteresting. And some researchers have paid inadequate attention to the fit of the measurement models they have specified within their structural models.

Heuristic SEM Application

To make this discussion concrete, heuristic SEM analyses involving the data reported by Bagozzi (1980) will be summarized (also see Jöreskog & Sörbom (1989, pp. 151-156)). The study investigated the job satisfaction and job performance of 122 workers. The relevant data are presented in Table 1.

INSERT TABLE 1 ABOUT HERE.

Here only selected models are evaluated to illustrate previously made ideas and to emphasize some new concepts as well. Given space considerations, all relevant analyses are not reported.

For example, here measurement model adequacy is not initially evaluated prior to structural equation modeling.

Here the primary model of interest is portrayed in Figure 1. This model will be referenced as Model A. In Model A, as is conventional, (a) measured/observed variables are designated within boxes, (b) latent/synthetic variables are represented within circles or ovals, and (c) correlations or covariances are represented by two-headed arrows.

INSERT FIGURE 1 ABOUT HERE.

Also as is conventional, measured/observed variables are taken as being the joint function of measurement error plus the underlying construct (thus the arrows proceed from the latent variables to the relevant measured variables, and not vice versa). This model asserts (a) that job satisfaction is a function of both achievement motivation and verbal intelligence, (b) that job performance is solely a function of task-specific self esteem, and that (c) job performance predicts job satisfaction, and not vice versa.

The relevant maximum-likelihood parameter estimates for this structural model are also presented in Table 2. Table 3 presents some fit statistics for this model (and others) for these data.

INSERT TABLES 2 AND 3 ABOUT HERE.

Variations on this model test are explored here to emphasize two major ideas. First, the integral and unique role of ***measurement error variance*** within structural equation modeling is explained and

explored. Second, the mechanisms and nature of SEM ***causal modeling*** are illustrated.

Role of Measurement Error Variance Within SEM

Too few researchers understand either what reliability is, or how reliability impacts statistical analyses. For example, some researchers persist in erroneously referring to the "reliability of the test" (see Reinhardt (1996), Thompson (1994), and especially Vacha-Haase (1998)).

In classical statistical analyses (e.g., ANOVA, regression, canonical correlation analysis), measurement error impacts parameter estimates and attenuates detected effect sizes (Thompson, 1994). But in classical analyses these measurement effects are not directly explored and evaluated. The primary distinguishing feature of structural equation modeling is that score reliability (i.e., [1 - measurement error variance] / total score variance) is directly considered (Stevens, 1996, p. 415).

In the present model, some of the measurement error variances (i.e., [1 - the score reliability coefficients] * the score variances) were "freed" to be estimated. For example, as reported in both Figure 1 and Table 2, the measurement error variance of the measured variable "Achievement Motivation measure #1" was estimated to be δ_1=2.571. Since the variance of this measured variable, reported in Table 1, was 3.802, the reliability coefficient for this measured/observed variable was poor (i.e., [1 - 2.571] / 3.802 = .324).

Also in Model A some measured variables were presumed to be

measured with perfect reliability (i.e., ϵ_i=0 for the measured job performance variable). But the measurement error variance for the measured "Verbal Intelligence Variable," although also "fixed" (i.e., not estimated), was not constrained to equal zero. Instead, a score reliability coefficient of .85 was presumed, based on previous reliability generalization research (Vacha-Haase, 1998) or some theoretical expectation. Therefore, the measurement error variance was "fixed" as 1.998 (i.e., [1 - .85] * the measured score variance of 13.323 reported in Table 1 = .15 * 13.323 = 1.998).

For heuristic purposes, a second model (Model B) was fit to the Table 1 data. The only difference in Model A and Model B was that score reliability for the measured variable, "Verbal Intelligence Variable," was "fixed" to zero in Model B (i.e., perfect score reliability on this measured variable was assumed). Table 2 also presents the parameter estimates for Model B.

Compare the Table 2 parameters estimated for these two models. Notice how changing just slightly the error variance for just one measured variables changes (at least slightly) the parameter estimates throughout the entire model.

Classical statistical analyses (e.g., ANOVA, canonical correlation analyses) presume no measurement error variance for any of the measured variables, while SEM models are usually specified to estimate and to take into account measurement error variance for all or most of the measured/observed variables. Think how different the parameter estimates even for the same data may therefore be across SEM as against non-SEM analyses, since usually all or none,

respectively, of the score reliability coefficients are taken into account in making parameter estimates! Which analytic model best honors a reality where measured/observed variables are not measured with perfect reliability?

SEM as "Causal Modeling"

As noted at the outset, historically some have referred to structural equation modeling as "causal modeling." Here the mechanisms for this thinking are illustrated. But some strong cautions are also noted.

Model A specified that the latent/synthetic variable "Job Performance" predicts "Job Satisfaction," and not vice versa. Model C was identical to Model A except that "Job Performance" and "Job Satisfaction" were presumed to reciprocally predict each other. Finally, Model D specified that "Job Satisfaction" predicts "Job Performance," and not vice versa.

The maximum-likelihood parameters estimates for these three models are all presented in Table 2. Table 3 presents various fit and other statistics for these three rival models. The tabled results indicate that Model D ("Job Satisfaction" predicts "Job Performance," and not vice versa) is less satisfactory than the other two models. For example, the chi-square and the chi-square-to-df ratio (1.556) is considerably inferior (i.e., larger) for Model D.

As regards the judgment between Model A and Model C, the critical issue involves the Wold or t statistics for the freed parameters. As reported in Table 3, the t value for estimating "Job

Satisfaction" predicted by "Job Performance" was 4.239 (.594 / .140). In Model C the same t value was 3.887 (.816 / 3.887). However, in Model C the t statistic for estimating "Job Performance" predicted by "Job Satisfaction" was |1.362| (|-.220| / .161). These results suggest that Model A may be more correctly specified.

But does this suggest that Model A is a superior "causal model"? Certainly some insight regarding causality might be inferred from the comparisons made here.

However, making such inferences would be extremely controversial. The view here is that definitive causal evidence can only be extrapolated from thoughtfully designed true experiments. Given a non-experimental design, such as yielded the present data, correlational analysis of such data yield inherently ambiguous causal results.

The argument can be framed as regards the context-specificity of all GLM weights (see Thompson (1998)). If we added or subtracted a single measured/observed variable, all the parameters might change quite dramatically. This is one aspect of model specification (i.e., are the exactly correct and only the exactly correct measured variables present?).

If we were certain that we had exactly (and only) the correct measured variables, then SEM might bear more powerfully on issues of causality. But as Pedhazur (1982) has noted, "The rub, however, is that the true model is seldom, if ever, known" (p. 229). And as Duncan (1975) has noted, "Indeed it would require no elaborate

sophistry to show that we will never have the 'right' model in any absolute sense" (p. 101).

The Ten Commandments for Good SEM Behavior

Huberty and Morris (1998) have observed that, "As in all of statistical inference, subjective judgment cannot be avoided. Neither can reasonableness!" (p. 573). This is true throughout the panorama of statistical methods. But judgment and reasonableness are especially the *sine qua non* of structural equation modeling.

Here some basic precepts and principles have been laid out to guide the novice modeler is exercising this judgment. Some of the principles can be summarized in the form of the following *10 Commandments for Good SEM Behavior*:

10. Don't use SEM with small samples.

9. Carefully consider the levels of scale and distributions of measured/observed variables when selecting the matrix of associations to be analyzed.

8. All things equal, prefer well-fitting more parsimonious models, since their fit is least an artifact of the model being nearly just-identified.

7. When using estimation theories requiring multivariate normality, use measured/observed variables that can be normally distributed, and empirically evaluate whether the distributional assumption is met.

6. Use multiple fit statistics, because several fit statistics consider different aspects or conceptions of fit, so that a judgment of correct specification will not be an artifact of analytic choice, and because we still have much to learn about the behavior of these statistics.

5. In evaluating model specification, in addition to considering statistical evidence, "assessment of model adequacy must be based on multiple criteria that [also] take into account theoretical... and practical considerations" (Byrne, 1998, p. 119) [i.e., remember that we define the constructs we use, and are responsible for making and defending these decisions].

4. Individually evaluate the measurement models prior to evaluating a structural equation model [but consider reformulating measurement models if structural modeling then suggests this may be appropriate].

3. Test multiple plausible rival models, so that stronger evidence supporting the correct specification of a model can be adduced.

2. Regarding specification searches, require larger samples, test the re-specified model with a "hold-out" or independent sample, and never change a specification unless you can offer a theoretical justification for the changes to the *a priori* model.

1. Never conclude that a model has been definitively proven, because infinitely many models can fit any given data set [thus, the fit of a single tested model is always an artifact of having tested too few models].

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Table 1
Pearson Correlation Coefficients, Standard Deviations,
and Variances/Covariances of the 8 Measured/Observed Variables

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	y1	y2	y3	x1	x2	x3	x4	x5
SD	2.09	3.43	2.81	1.95	2.06	2.16	2.06	3.65
y1	1.000[a]							
	2.090[b]							
	2.090[c]							
	4.368[d]							
y2	0.418	1.000						
	2.090	3.430						
	3.430	3.430						
	2.997	11.765						
y3	0.394	0.627	1.000					
	2.090	3.430	2.810					
	2.810	2.810	2.810					
	2.314	6.043	7.896					
x1	0.129	0.202	0.266	1.000				
	2.090	3.430	2.810	1.950				
	1.950	1.950	1.950	1.950				
	0.526	1.351	1.458	3.802				
x2	0.189	0.284	0.208	0.365	1.000			
	2.090	3.430	2.810	1.950	2.060			
	2.060	2.060	2.060	2.060	2.060			
	0.814	2.007	1.204	1.466	4.244			
x3	0.544	0.281	0.324	0.201	0.161	1.000		
	2.090	3.430	2.810	1.950	2.060	2.160		
	2.160	2.160	2.160	2.160	2.160	2.160		
	2.456	2.082	1.967	0.847	0.716	4.666		
x4	0.507	0.225	0.314	0.172	0.174	0.546	1.000	
	2.090	3.430	2.810	1.950	2.060	2.160	2.060	
	2.060	2.060	2.060	2.060	2.060	2.060	2.060	
	2.183	1.590	1.818	0.691	0.738	2.429	4.244	
x5	-0.357	-0.156	-0.038	-0.199	-0.277	-0.294	-0.174	1.000
	2.090	3.430	2.810	1.950	2.060	2.160	2.060	3.650
	3.650	3.650	3.650	3.650	3.650	3.650	3.650	3.650
	-2.723	-1.953	-0.390	-1.416	-2.083	-2.318	-1.308	13.323

Note. "y1" = Performance measure; "y2" = Job Satisfaction measure #1; "y3" = Job Satisfaction measure #2; "x1" = Achievement Motivation measure #1; "x2" = Achievement Motivation measure #2; "x3" = Task-specific Self Esteem measure #1; "x4" = Task-specific Self Esteem measure #2; "x5" = Verbal Intelligence measure.

[a]Pearson r between two measured/observed variables ($r_{XY} = COV_{XY} / (SD_X \times SD_Y)$)

[b]Standard deviation of one measured/observed variable in a given variable pair

[c]Standard deviation of the other measured/observed variable in a given variable pair

[d]Variance of a given measured/observed variable, if on the diagonal, or the covariance between two measured/observed variables ($COV_{XY} = r_{XY} (SD_X) (SD_Y)$), if off-diagonal

Table 2
Parameter Estimates for 4 Model Variations

Maximum-Likelihood Freed/Estimated and the Fixed, Non-zero (in Parentheses) Parameters for the Figure 1 Model (Performance Predicts Job Satisfaction; *Reliability of Verbal Intelligence (X_5) Scores Fixed as .85*) [see Appendix B for the LISREL commands and results]

Predictor Measurement Error Variances	Predictor Measurement Parameters	Predictor Synthetic Covariances	Predictor Construct Path Coefficients
δ_1=2.571	($\lambda_{1,1}$=1)	$\phi_{2,1}$=0.751	$\gamma_{2,1}$=1.228
δ_2=2.566	$\lambda_{2,1}$=1.168	$\phi_{3,1}$=-1.627	$\gamma_{2,3}$=0.213
(δ_5=1.998)	($\lambda_{5,3}$=1)	$\phi_{3,2}$=-2.303	$\gamma_{1,2}$=0.923
δ_3=1.931	($\lambda_{3,2}$=1)		
δ_4=2.213	$\lambda_{4,2}$=0.862		

Criterion Synthetic Path Coefficients	Criterion Synthetic Error Variances	Criterion Measurement Parameters	Criterion Measurement Error Variances
$\beta_{2,1}$=0.594	ζ_2=3.865	($\lambda_{2,2}$=1)	ϵ_2=4.492
	ζ_1=2.038	$\lambda_{3,2}$=0.831	ϵ_3=2.875
		($\lambda_{1,1}$=1)	[ϵ_1=0]

Maximum-Likelihood Freed/Estimated and the Fixed, Non-zero (in Parentheses) Parameters for the Model that Performance Predicts Job Satisfaction with *Reliability of Verbal Intelligence Scores (X_5) Fixed as 1.0* [see Appendix C for the LISREL commands and results]

Predictor Measurement Error Variances	Predictor Measurement Parameters	Predictor Synthetic Covariances	Predictor Construct Path Coefficients
δ_1=2.571	($\lambda_{1,1}$=1)	$\phi_{2,1}$=0.747	$\gamma_{2,1}$=1.179
δ_2=2.562	$\lambda_{2,1}$=1.169	$\phi_{3,1}$=-1.628	$\gamma_{2,3}$=0.175
==> [δ_5=0]	($\lambda_{5,3}$=1)	$\phi_{3,2}$=-2.316	$\gamma_{1,2}$=0.923
δ_3=1.930	($\lambda_{3,2}$=1)		
δ_4=2.215	$\lambda_{4,2}$=0.861		

Criterion Synthetic Path Coefficients	Criterion Synthetic Error Variances	Criterion Measurement Parameters	Criterion Measurement Error Variances
$\beta_{2,1}$=0.583	ζ_2=3.925	($\lambda_{2,2}$=1)	ϵ_2=4.517
	ζ_1=2.038	$\lambda_{3,2}$=0.834	ϵ_3=2.858
		($\lambda_{1,1}$=1)	[ϵ_1=0]

Table 2 (cont.)

Maximum-Likelihood Freed/Estimated and the Fixed, Non-zero (in Parentheses) Parameters for the Model that *Performance and Job Satisfaction Reciprocally Predict Each Other* with Reliability of Verbal Intelligence Scores (X_5) Fixed as .85 [see Appendix D for the LISREL commands and results]

Predictor Measurement Error Variances	Predictor Measurement Parameters	Predictor Synthetic Covariances	Predictor Construct Path Coefficients
δ_1=2.506	($\lambda_{1,1}$=1)	$\phi_{2,1}$=0.773	$\gamma_{2,1}$=1.057
δ_2=2.566	$\lambda_{2,1}$=1.138	$\phi_{3,1}$=-1.648	$\gamma_{2,3}$=0.265
[δ_5=1.998]	($\lambda_{5,3}$=1)	$\phi_{3,2}$=-2.235	$\gamma_{1,2}$=1.111
δ_3=1.955	($\lambda_{3,2}$=1)		
δ_4=2.212	$\lambda_{4,2}$=0.866		

	Criterion Synthetic Path Coefficients	Criterion Synthetic Error Variances	Criterion Measurement Parameters	Criterion Measurement Error Variances
==========>	$\beta_{2,1}$=0.816	ζ_2=3.904	($\lambda_{2,2}$=1)	ϵ_2=4.921
	$\beta_{1,2}$=-.220	ζ_1=2.573	$\lambda_{3,2}$=0.881	ϵ_3=2.578
			($\lambda_{1,1}$=1)	[ϵ_1=0]

Maximum-Likelihood Freed/Estimated and the Fixed, Non-zero (in Parentheses) Parameters for the Model that *Job Satisfaction Predicts Performance* with Reliability of Verbal Intelligence (X_5) Scores Fixed as .85 [see Appendix E for the LISREL commands and results]

Predictor Measurement Error Variances	Predictor Measurement Parameters	Predictor Synthetic Covariances	Predictor Construct Path Coefficients
δ_1=3.123	($\lambda_{1,1}$=1)	$\phi_{2,1}$=0.870	$\gamma_{2,1}$=3.208
δ_2=3.293	$\lambda_{2,1}$=1.184	$\phi_{3,1}$=-1.629	$\gamma_{2,3}$=0.348
[δ_5=1.998]	($\lambda_{5,3}$=1)	$\phi_{3,2}$=-2.296	$\gamma_{1,2}$=0.801
δ_3=1.911	($\lambda_{3,2}$=1)		
δ_4=2.214	$\lambda_{4,2}$=0.858		

	Criterion Synthetic Path Coefficients	Criterion Synthetic Error Variances	Criterion Measurement Parameters	Criterion Measurement Error Variances
==========>	$\beta_{1,2}$=0.150	ζ_2=4.475	($\lambda_{2,2}$=1)	ϵ_2=4.475
	[$\beta_{2,1}$=0]	ζ_1=2.822	$\lambda_{3,2}$=0.834	ϵ_3=2.822
			($\lambda_{1,1}$=1)	[ϵ_1=0]

Table 3
A Few Fit Statistics for the Three
Substantively Competitive Models (A, C, D)

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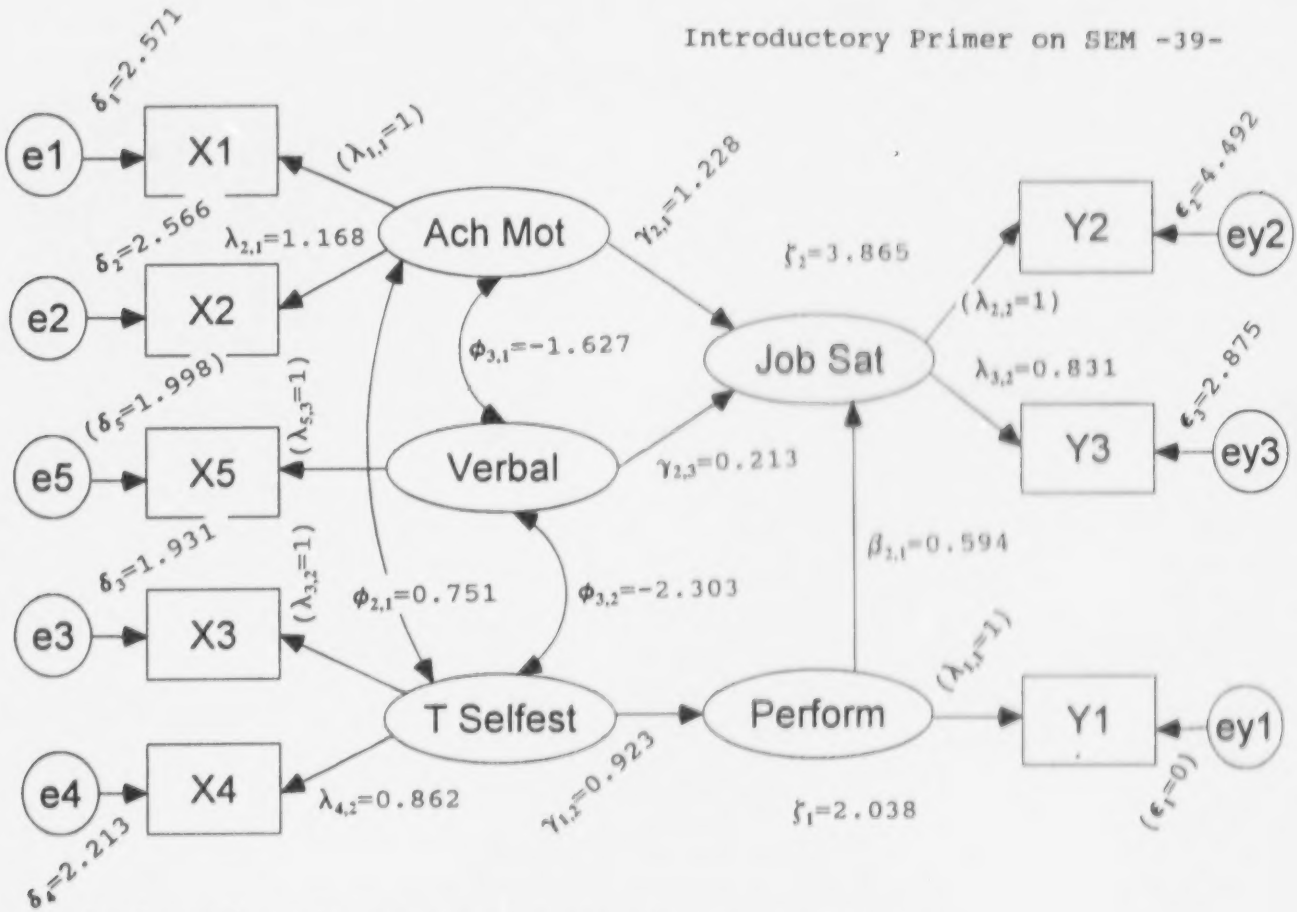
Statistic	Model		
	A	C	D
chi square	14.19	12.12	23.34
n of parameter estimates	21	22	21
df	15	14	15
chi square to df ratio	0.946	0.866	1.556
goodness of fit index (GFI)	0.969	0.974	0.953
adjusted goodness of fit index (AGFI)	0.926	0.932	0.886
root mean-square residual (RMR)	0.285	0.287	0.304
coef of determination for 5 X variables	0.974	0.974	0.961
coef of determination for structural equations	0.663	0.547	0.797
$\beta_{(2,1)}$	0.594	0.816	--
SE $\beta_{(2,1)}$	0.140	0.210	--
$\beta_{(2,1)}$ / SE	4.239	3.887	--
$\beta_{(1,2)}$	--	-0.220	0.150
SE $\beta_{(1,2)}$	--	0.161	0.078
$\beta_{(1,2)}$ / SE	--	-1.362	1.928

Note. With 8 observed variables, available degrees of freedom equal 36 ([8 * 9] / 2). If, for example, 21 parameters are estimated, the model's degrees of freedom equal 15 (36 - 21).



Declaration of Freed/Estimated (**in Greek letters**) and Fixed (**numbers**) Model Parameters

Theta Delta

$$\begin{bmatrix} \delta_1 \\ \delta_2 \\ 1.998_5 \\ \delta_3 \\ \delta_4 \end{bmatrix}$$

Lambda X

$$\begin{bmatrix} 1_{1,1} & 0_{1,2} & 0_{1,3} \\ \lambda_{2,1} & 0_{2,2} & 0_{2,3} \\ 0_{5,1} & 0_{5,2} & 1_{5,3} \\ 0_{3,1} & 1_{3,2} & 0_{3,3} \\ 0_{4,1} & \lambda_{4,2} & 0_{4,3} \end{bmatrix}$$

Phi

$$\begin{bmatrix} \phi_{1,1} & & \\ \phi_{2,1} & \phi_{2,2} & \\ \phi_{3,1} & \phi_{3,2} & \phi_{3,3} \end{bmatrix}$$

Gamma

$$\begin{bmatrix} 0_{1,1} & \gamma_{1,2} & 0_{1,3} \\ \gamma_{2,1} & 0_{2,2} & \gamma_{2,3} \end{bmatrix}$$

Beta

$$\begin{bmatrix} 0_{1,1} & 0_{1,2} \\ \beta_{2,1} & 0_{2,2} \end{bmatrix}$$

Psi

$$\begin{bmatrix} \zeta_1 & \zeta_2 \end{bmatrix}$$

Lambda Y

$$\begin{bmatrix} 1_{1,1} & 0_{1,2} \\ 0_{2,1} & 1_{2,2} \\ 0_{3,1} & \lambda_{3,2} \end{bmatrix}$$

Theta Epsilon

$$\begin{bmatrix} 0_1 \\ \epsilon_2 \\ \epsilon_3 \end{bmatrix}$$

N.B. Given the reliability of the Verbal Intelligence scores was fixed (constrained) as equaling .85, the fixed error variance for this variable in this model equals the variance of this measured variable (13.323 from Table 1) times (1 - .85) [(1 - .85) 13.323 = (.15) 13.323 = 1.998].

Figure 1
Performance Predicts Job Satisfaction;
Reliability of Verbal Intelligence Scores Fixed as .85

Appendix A
SPSS for Windows Version of Program MULTINOR to Evaluate Multivariate Normality

multino2.aer 10/11/97

multinor.sps

```
SET BLANKS=SYSMIS UNDEFINED=WARN printback=list.
TITLE 'MULTINOR.SPS   tests multivar normality graphically****'.
COMMENT ***********************************************************.
COMMENT The original MULTINOR computer program was presented,
COMMENT with examples, in:
COMMENT     Thompson, B. (1990). MULTINOR: A FORTRAN program that
COMMENT     assists in evaluating multivariate normality.
COMMENT      Educational and Psychological Measurement_, 50,
COMMENT     845-848.
COMMENT
COMMENT The logic and the data source for the example are from:
COMMENT     Stevens, J. (1986). _Applied multivariate statistics
COMMENT     for the social sciences_. Hillsdale, NJ: Erlbaum.
COMMENT     (pp. 207-212)
COMMENT ***********************************************************.
COMMENT  Here there are 3 variables for which multivariate
COMMENT  normality is being confirmed.
COMMENT       Note. The number of cases in actual practice should be
COMMENT  at least 25-30 for the graphical procedure to function
COMMENT  effectively.
DATA LIST
  FILE='c:\spsswin\multinor.dat' FIXED RECORDS=1 TABLE
  /1 x1 1-3 (1) x2 5-7 (1) x3 9-11 (1).
list variables=all/cases=9999/format=numbered .
COMMENT  'y' is a variable automatically created by the program, and
COMMENT  does not have to modified for different data sets.
compute y=$casenum .
print formats y(F5) .
regression variables=y x1 to x3/
  descriptive=mean stddev corr/
  dependent=y/enter x1 to x3/
  save=mahal(mahal) .
sort cases by mahal(a) .
execute .
list variables=y x1 to x3 mahal/cases=9999/format=numbered .
COMMENT  In the next TWO lines, for a given data set put the actual n
COMMENT  in place of the number '12' used for the example data set.
loop #i=1 to 12 .
COMMENT  In the next line, change '3' to whatever is the number
COMMENT  of variables.
COMMENT       The p critical value of chi square for a given case
COMMENT  is set as [the case number (after sorting) - .5] / the
COMMENT  sample size].
compute p=($casenum - .5) / 12. .
compute chisq=idf.chisq(p,3) .
end loop .
print formats p chisq (F8.5) .
list variables=y p mahal chisq/cases=9999/format=numbered .
plot
  vertical='chi square'/
  horizontal='Mahalabis distance'/
  plot=chisq with mahal .
```

multinor.dat

```
2.4 2.1 2.4
3.5 1.8 3.9
6.7 3.6 5.9
5.3 3.3 6.1
5.2 4.1 6.4
3.2 2.7 4.0
4.5 4.9 5.7
3.9 4.7 4.7
4.0 3.6 2.9
5.7 5.5 6.2
2.4 2.9 3.2
2.7 2.6 4.1
```

multinor.lst

```
-> SET BLANKS=SYSMIS UNDEFINED=WARN printback=list.

-> TITLE 'MULTINOR.SPS   tests multivar normality graphically****'.

-> COMMENT ************************************************************.
-> COMMENT The original MULTINOR computer program was presented,
-> COMMENT with examples, in:
-> COMMENT      Thompson, B. (1990). MULTINOR: A FORTRAN program that
-> COMMENT      assists in evaluating multivariate normality.
-> COMMENT       Educational and Psychological Measurement_, 50,
-> COMMENT      845-848.
-> COMMENT
-> COMMENT The logic and the data source for the example are from:
-> COMMENT      Stevens, J. (1986). _Applied multivariate statistics
-> COMMENT      for the social sciences_. Hillsdale, NJ: Erlbaum.
-> COMMENT      (pp. 207-212)
-> COMMENT ************************************************************.

-> COMMENT  Here there are 3 variables for which multivariate
-> COMMENT  normality is being confirmed.

-> DATA LIST
->   FILE='c:\spsswin\multinor.dat' FIXED RECORDS=1 TABLE
->   /1 x1 1-3 (1) x2 5-7 (1) x3 9-11 (1).

-> list variables=all/cases=9999/format=numbered .

      X1   X2   X3
  1  2.4  2.1  2.4
  2  3.5  1.8  3.9
  3  6.7  3.6  5.9
  4  5.3  3.3  6.1
  5  5.2  4.1  6.4
  6  3.2  2.7  4.0
  7  4.5  4.9  5.7
  8  3.9  4.7  4.7
  9  4.0  3.6  2.9
 10  5.7  5.5  6.2
 11  2.4  2.9  3.2
 12  2.7  2.6  4.1

Number of cases read:  12    Number of cases listed:  12

-> COMMENT  'y' is a variable automatically created by the program, and
-> COMMENT  does not have to modified for different data sets.

-> compute y=$casenum .
```

```
-> print formats y(F5) .

-> regression variables=y x1 to x3/
->   descriptive=mean stddev corr/
->   dependent=y/enter x1 to x3/
->   save=mahal(mahal) .

          * * * *  M U L T I P L E  R E G R E S S I O N  * * * *
Listwise Deletion of Missing Data
           Mean   Std Dev  Label
Y         6.500    3.606
X1        4.125    1.384
X2        3.483    1.147
X3        4.625    1.406

N of Cases =     12

Correlation:
                Y         X1         X2         X3
Y           1.000      -.207       .376      -.044
X1          -.207      1.000       .606       .845
X2           .376       .606      1.000       .656
X3          -.044       .845       .656      1.000

          * * * *  M U L T I P L E  R E G R E S S I O N  * * * *

Equation Number 1    Dependent Variable..   Y
  Descriptive Statistics are printed on Page   83

Block Number  1.  Method:  Enter      X1        X2        X3

Variable(s) Entered on Step Number
   1..     X3
   2..     X2
   3..     X1

Multiple R              .66417
R Square                .44112
Adjusted R Square       .23154
Standard Error         3.16069

Analysis of Variance
                 DF        Sum of Squares        Mean Square
Regression        3             63.08053           21.02684
Residual          8             79.91947            9.98993

F =       2.10480        Signif F =  .1780

------------------ Variables in the Equation ------------------

Variable             B         SE B        Beta          T  Sig T

X1           -1.909097     1.296480    -.733029     -1.473  .1791
X2            2.445453     1.110369     .778083      2.202  .0588
X3             .165296     1.345478     .064454       .123  .9053
(Constant)    5.092203     3.454771                  1.474  .1787

End Block Number   1   All requested variables entered.

          * * * *  M U L T I P L E  R E G R E S S I O N  * * * *
Equation Number 1    Dependent Variable..   Y

Residuals Statistics:
```

	Min	Max	Mean	Std Dev	N
*PRED	2.0801	9.9172	6.5000	2.3947	12
*ZPRED	-1.8457	1.4270	.0000	1.0000	12
*SEPRED	1.2118	2.4798	1.7932	.3534	12
*ADJPRED	.6074	10.6661	6.2406	2.9511	12
*RESID	-5.0425	5.0265	.0000	2.6954	12
*ZRESID	-1.5954	1.5903	.0000	.8528	12
*SRESID	-1.9334	1.8781	.0291	1.0420	12
*DRESID	-7.4057	7.0104	.2594	4.0901	12
*SDRESID	-2.4778	2.3496	.0287	1.2152	12
***MAHAL**	**.7004**	**5.8543**	**2.7500**	**1.5070**	**12**
*COOK D	.0000	.4543	.1364	.1713	12
*LEVER	.0637	.5322	.2500	.1370	12

Total Cases = 12

* *

From Equation 1: 1 new variables have been created.

Name	Contents
MAHAL	Mahalanobis' Distance

```
-> sort cases by mahal(a) .
-> execute .

-> list variables=x1 to x3 mahal/cases=9999/format=numbered .
```

	X1	X2	X3	MAHAL
1	3.2	2.7	4.0	.70038
2	2.4	2.9	3.2	1.65042
3	5.2	4.1	6.4	1.98854
4	3.9	4.7	4.7	2.17303
5	2.7	2.6	4.1	2.19634
6	4.5	4.9	5.7	2.22174
7	5.3	3.3	6.1	2.37118
8	3.5	1.8	3.9	2.53196
9	2.4	2.1	2.4	2.59346
10	5.7	5.5	6.2	3.12622
11	4.0	3.6	2.9	5.59246
12	6.7	3.6	5.9	5.85428

```
Number of cases read:  12    Number of cases listed:  12

-> COMMENT  In the next TWO lines, for a given data set put the actual
-> COMMENT  in place of the number '12' used for the example data set.

-> loop #i=1 to 12 .

-> COMMENT  In the next line, change '3' to whatever is the number
-> COMMENT  of variables.
-> COMMENT       The p critical value of chi square for a given case
-> COMMENT  is set as [the case number (after sorting) - .5] / the
-> COMMENT  sample size].

-> compute p=($casenum - .5) / 12. .

-> compute chisq=idf.chisq(p,3) .

-> end loop .

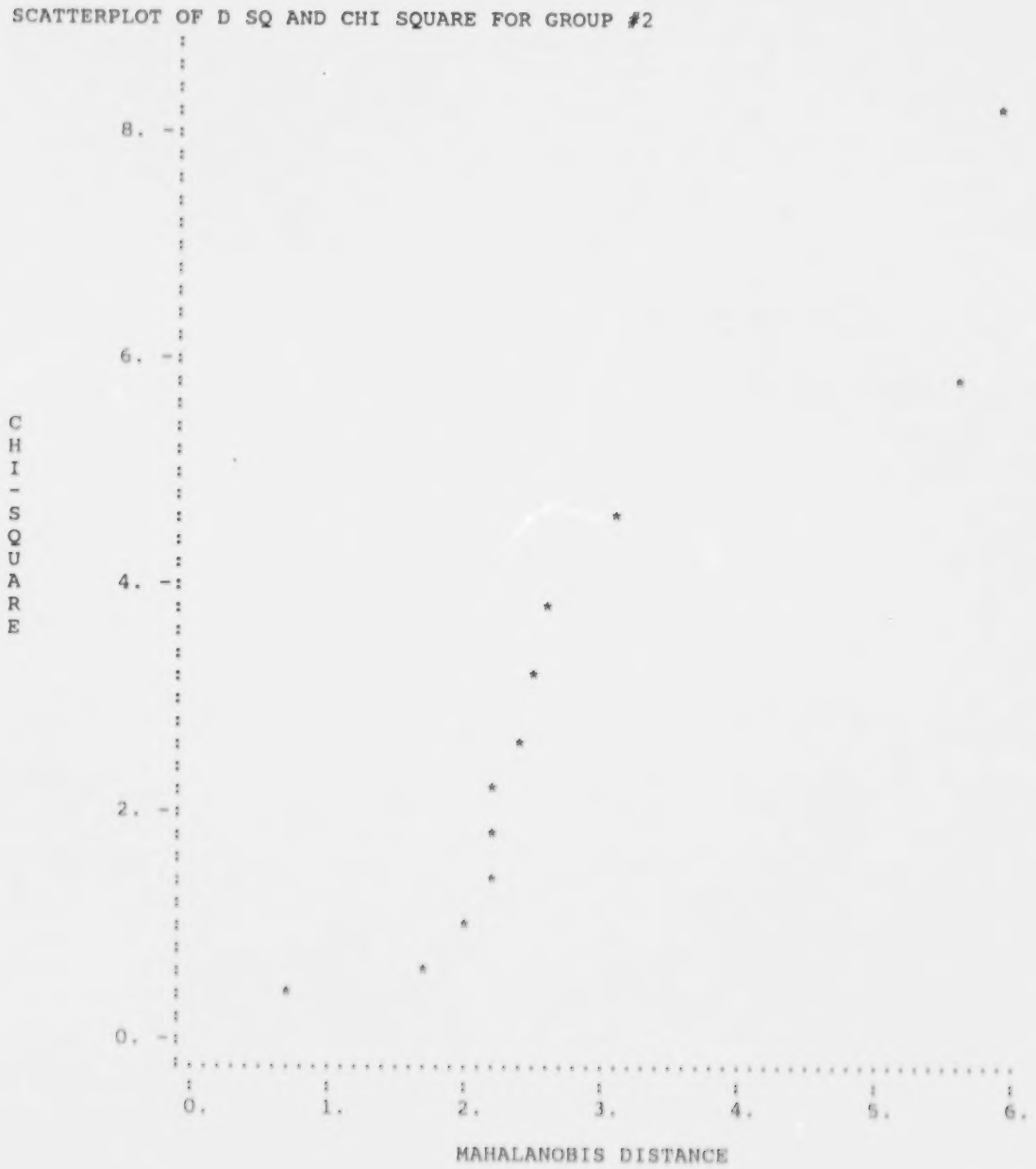
-> print formats p chisq (F8.5) .
```

```
-> list variables=y p mahal chisq/cases=9999/format=numbered .
          Y         P        MAHAL     CHISQ
     1    6    .04167       .70038    .30897
     2   11    .12500      1.65042    .69236
     3    5    .20833      1.98854   1.03962
     4    8    .29167      2.17303   1.38807
     5   12    .37500      2.19634   1.75398
     6    7    .45833      2.22174   2.15099
     7    4    .54167      2.37118   2.59519
     8    2    .62500      2.53196   3.10983
     9    1    .70833      2.59346   3.73392
    10   10    .79167      3.12622   4.54475
    11    9    .87500      5.59246   5.73941
    12    3    .95833      5.85428   8.22056

Number of cases read:  12    Number of cases listed:  12


-> plot
->   vertical='chi square'/
->   horizontal='Mahalabis distance'/
->   plot=chisq with mahal .

Hi-Res Chart  # 6:Plot of chisq with mahal
```



Note. For data sets involving at least 25-30 data points, the graph will define a straight line for multivariate normal data.

Appendix B
Maximum-Likelihood Analysis for the Figure 1 Model
(Performance Predicts Job Satisfaction;
Reliability of Verbal Intelligence (X_1) Scores Fixed as .85)

lisr152a.lst 7/9/98

```
08-Jul-98   SPSS RELEASE 4.1 FOR IBM OS/MVS                                    Page   1
15:44:29    TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

For MVS/ESA/JES3        TEXAS A&M UNIVERSITY: CIS          License Number 1267
This software is functional through August 31, 1998.

   1  0  title 'LISR152a.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156'
   2  0  data list file=abc records=3 table/1 id 1-4
   3  0    /2 /3
This command will read 3 records from 'E100BT.ARTHUR.DAT'
Variable   Rec   Start     End         Format

ID           1       1       4         F4.0

   4  0  lisrel
   5  0    /"Joreskog/Sorbom pp. 155-156 Model *****"
   6  0    /DA NI=8 NO=122 MA=CM
   7  0    /LA
   8  0    /'PERFORMM' 'JBSATIS1' 'JBSATIS2' 'ACHIMOT1'
   9  0    /'ACHIMOT2' 'TASKSEL1' 'TASKSEL2' 'VERBALIQ'
  10  0    /KM SY
  11  0    /(8F8.3)
  12  0    /   4.368
  13  0    /   2.997  11.765
  14  0    /   2.314   6.043   7.896
  15  0    /   0.526   1.351   1.458   3.802
  16  0    /   0.814   2.007   1.204   1.466   4.244
  17  0    /   2.456   2.082   1.967   0.847   0.716   4.666
  18  0    /   2.183   1.590   1.818   0.691   0.738   2.429   4.244
  19  0    /  -2.723  -1.953  -0.390  -1.416  -2.083  -2.318  -1.308  13.323
  20  0    /MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
  21  0    /LE
  22  0    /'PERFORMN' 'JOBSATIS'
  23  0    /LK
  24  0    /'AMOTIVAT' 'TASKSELF' 'VERBINTL'
  25  0    /FR LY(3,2) LX(2,1) LX(4,2) BE(2,1)
  26  0    /FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
  27  0    /VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
  28  0    /VA 1.998 TD(5,5)
  29  0    /OU SE SS SC TV MI ND=3
There are 3,033,288 bytes of memory available.
The largest contiguous area has 3,026,960 bytes.


                LISREL 7:  ESTIMATION OF LINEAR STRUCTURAL EQUATION SYSTEMS
                        PROGRAM VERSION 7.16       DISTRIBUTED BY

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MVS - L I S R E L 7.16
BY
KARL G JORESKOG AND DAG SORBOM

THE FOLLOWING LISREL CONTROL LINES HAVE BEEN READ :

```
Joreskog/Sorbom pp. 155-156 Model ****
DA NI=8 NO=122 MA=CM
LA
PERFORMM   JBSATIS1   JBSATIS2   ACHIMOT1
ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
KM SY
(8F8.3)
MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
LE
PERFORMN   JOBSATIS
LK
AMOTIVAT   TASKSELF   VERBINTL
FR LY(3,2) LX(2,1) LX(4,2) BE(2,1)
FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
VA 1.998 TD(5,5)
OU SE SS SC TV MI ND=3
```

Joreskog/Sorbom pp. 155-156 Model ****

NUMBER OF INPUT VARIABLES 8
NUMBER OF Y - VARIABLES 3
NUMBER OF X - VARIABLES 5
NUMBER OF ETA - VARIABLES 2
NUMBER OF KSI - VARIABLES 3
NUMBER OF OBSERVATIONS 122

Joreskog/Sorbom pp. 155-156 Model ****

COVARIANCE MATRIX TO BE ANALYZED

	PERFORMM	JBSATIS1	JBSATIS2	ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
PERFORMM	4.368							
JBSATIS1	2.997	11.765						
JBSATIS2	2.314	6.043	7.896					
ACHIMOT1	0.526	1.351	1.458	3.802				
ACHIMOT2	0.814	2.007	1.204	1.466	4.244			
TASKSEL1	2.456	2.082	1.967	0.847	0.716	4.666		
TASKSEL2	2.183	1.590	1.818	0.691	0.738	2.429	4.244	
VERBALIQ	-2.723	-1.953	-0.390	-1.416	-2.083	-2.318	-1.308	13.323

Joreskog/Sorbom pp. 155-156 Model ****

PARAMETER SPECIFICATIONS

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0	0
JBSATIS1	0	0
JBSATIS2	0	1

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0	0	0
ACHIMOT2	2	0	0
TASKSEL1	0	0	0
TASKSEL2	0	3	0
VERBALIQ	0	0	0

BETA

	PERFORMN	JOBSATIS
PERFORMN	0	0
JOBSATIS	4	0

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0	5	0
JOBSATIS	6	0	7

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	8		
TASKSELF	9	10	
VERBINTL	11	12	13

PSI

PERFORMN	JOBSATIS
14	15

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0	16	17

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
18	19	20	21	0

Joreskog/Sorbom pp. 155-156 Model ****
INITIAL ESTIMATES (TSLS)

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	1.000
JBSATIS2	0.000	0.797

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	1.000	0.000	0.000
ACHIMOT2	0.877	0.000	0.000
TASKSEL1	0.000	1.000	0.000
TASKSEL2	0.000	0.939	0.000
VERBALIQ	0.000	0.000	1.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.707	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.926	0.000
JOBSATIS	0.989	0.000	0.208

COVARIANCE MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	4.368				
JOBSATIS	3.478	8.316			
AMOTIVAT	0.759	1.810	1.671		
TASKSELF	2.395	2.114	0.820	2.587	
VERBINTL	-1.744	-0.692	-1.833	-1.885	11.325

PSI

PERFORMN	JOBSATIS
2.151	4.209

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	4.181	3.081

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
2.131	2.958	2.079	1.963	1.998

SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES

PERFORMM	JBSATIS1	JBSATIS2

```
          1.000       0.665       0.632
      SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES
         ACHIMOT1    ACHIMOT2    TASKSEL1    TASKSEL2    VERBALIQ
          0.440       0.303       0.554       0.537       0.850
      TOTAL COEFFICIENT OF DETERMINATION FOR X - VARIABLES IS  0.976
      SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS
         PERFORMN    JOBSATIS
          0.507       0.494
      TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS  IS  0.626
Joreskog/Sorbom pp. 155-156 Model ****

LISREL ESTIMATES (MAXIMUM LIKELIHOOD)
      LAMBDA Y
         PERFORMN    JOBSATIS

PERFORMN      1.000       0.000
JBSATIS1      0.000       1.000
JBSATIS2      0.000       0.831
      LAMBDA X
         AMOTIVAT    TASKSELF    VERBINTL

ACHIMOT1      1.000       0.000       0.000
ACHIMOT2      1.168       0.000       0.000
TASKSEL1      0.000       1.000       0.000
TASKSEL2      0.000       0.862       0.000
VERBALIQ      0.000       0.000       1.000
      BETA
         PERFORMN    JOBSATIS

PERFORMN      0.000       0.000
JOBSATIS      0.594       0.000
      GAMMA
         AMOTIVAT    TASKSELF    VERBINTL

PERFORMN      0.000       0.923       0.000
JOBSATIS      1.228       0.000       0.213
      COVARIANCE MATRIX OF ETA AND KSI
         PERFORMN    JOBSATIS    AMOTIVAT    TASKSELF    VERBINTL

PERFORMN      4.368
JOBSATIS      2.995       7.401
AMOTIVAT      0.694       1.577       1.231
TASKSELF      2.524       1.932       0.751       2.735
VERBINTL     -2.125      -0.845      -1.627      -2.303      11.327
      PSI
         PERFORMN    JOBSATIS

          2.038       3.865
      THETA EPS
         PERFORMN    JBSATIS1    JBSATIS2

          0.000       4.492       2.875
      THETA DELTA
         ACHIMOT1    ACHIMOT2    TASKSEL1    TASKSEL2    VERBALIQ

          2.571       2.566       1.931       2.213       1.998
      SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES
         PERFORMN    JBSATIS1    JBSATIS2

          1.000       0.622       0.640
      SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES
         ACHIMOT1    ACHIMOT2    TASKSEL1    TASKSEL2    VERBALIQ

          0.324       0.395       0.586       0.479       0.850
      TOTAL COEFFICIENT OF DETERMINATION FOR X - VARIABLES IS  0.974
      SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS
         PERFORMN    JOBSATIS
```

```
          0.533       0.478
       TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS  IS  0.663
W_A_R_N_I_N_G : THETA EPS is not positive definite


        CHI-SQUARE WITH  15 DEGREES OF FREEDOM =    14.19 (P = .511)
                    GOODNESS OF FIT INDEX =0.969
               ADJUSTED GOODNESS OF FIT INDEX =0.926
                   ROOT MEAN SQUARE RESIDUAL =     0.285

Joreskog/Sorbom pp. 155-156 Model ****
SUMMARY STATISTICS FOR FITTED RESIDUALS
SMALLEST FITTED RESIDUAL =   -1.108
  MEDIAN FITTED RESIDUAL =    0.000
 LARGEST FITTED RESIDUAL =    0.676
STEMLEAF PLOT
-10|1
 - 8|
 - 6|0
 - 4|
 - 2|33
 - 0|8776319772200000000
   0|13470557
   2|116
   4|3
   6|8
SUMMARY STATISTICS FOR STANDARDIZED RESIDUALS
SMALLEST STANDARDIZED RESIDUAL =   -2.053
  MEDIAN STANDARDIZED RESIDUAL =    0.000
 LARGEST STANDARDIZED RESIDUAL =    1.825
STEMLEAF PLOT
 - 2|1
 - 1|8
 - 1|3322
 - 0|87777
 - 0|222110000000
   0|1234
   0|55778
   1|012
   1|8
Joreskog/Sorbom pp. 155-156 Model ****

STANDARD ERRORS
        LAMBDA Y
           PERFORMN    JOBSATIS
           --------    --------
PERFORMN      0.000       0.000
JBSATIS1      0.000       0.000
JBSATIS2      0.000       0.134
        LAMBDA X
           AMOTIVAT    TASKSELF    VERBINTL
           --------    --------    --------
ACHIMOT1      0.000       0.000       0.000
ACHIMOT2      0.336       0.000       0.000
TASKSEL1      0.000       0.000       0.000
TASKSEL2      0.000       0.138       0.000
VERBALIQ      0.000       0.000       0.000
        BETA
           PERFORMN    JOBSATIS
           --------    --------
PERFORMN      0.000       0.000
JOBSATIS      0.140       0.000
        GAMMA
           AMOTIVAT    TASKSELF    VERBINTL
           --------    --------    --------
PERFORMN      0.000       0.144       0.000
JOBSATIS      0.477       0.000       0.107
        PHI
           AMOTIVAT    TASKSELF    VERBINTL
```

AMOTIVAT	0.500		
TASKSELF	0.298	0.646	
VERBINTL	0.592	0.683	1.713

PSI

	PERFORMN	JOBSATIS
	0.396	1.222

THETA EPS

	PERFORMN	JBSATIS1	JBSATIS2
	0.000	1.177	0.799

THETA DELTA

	ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
	0.479	0.574	0.425	0.388	0.000

Joreskog/Sorbom pp. 155-156 Model ****

T-VALUES

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JBSATIS1	0.000	0.000
JBSATIS2	0.000	6.195

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	0.000	0.000
ACHIMOT2	3.474	0.000	0.000
TASKSEL1	0.000	0.000	0.000
TASKSEL2	0.000	6.254	0.000
VERBALIQ	0.000	0.000	0.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	4.239	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	6.395	0.000
JOBSATIS	2.572	0.000	2.000

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	2.464		
TASKSELF	2.520	4.236	
VERBINTL	-2.749	-3.373	6.612

PSI

	PERFORMN	JOBSATIS
	5.145	3.163

THETA EPS

	PERFORMN	JBSATIS1	JBSATIS2
	0.000	3.816	3.599

THETA DELTA

	ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
	5.371	4.468	4.549	5.702	0.000

Joreskog/Sorbom pp. 155-156 Model ****

STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMN	2.090	0.000
JBSATIS1	0.000	2.720
JBSATIS2	0.000	2.260

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	1.109	0.000	0.000
ACHIMOT2	1.296	0.000	0.000
TASKSEL1	0.000	1.654	0.000
TASKSEL2	0.000	1.425	0.000
VERBALIQ	0.000	0.000	3.366

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.457	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.501	0.000	0.264

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.527	1.000			
AMOTIVAT	0.299	0.522	1.000		
TASKSELF	0.730	0.429	0.410	1.000	
VERBINTL	-0.302	-0.092	-0.436	-0.414	1.000

PSI

PERFORMN	JOBSATIS
0.467	0.522

REGRESSION MATRIX ETA ON KSI (STANDARDIZED)

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.501	0.333	0.264

Joreskog/Sorbom pp. 155-156 Model ****

COMPLETELY STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	0.789
JBSATIS2	0.000	0.800

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.569	0.000	0.000
ACHIMOT2	0.629	0.000	0.000
TASKSEL1	0.000	0.766	0.000
TASKSEL2	0.000	0.692	0.000
VERBALIQ	0.000	0.000	0.922

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.457	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.501	0.000	0.264

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.527	1.000			
AMOTIVAT	0.299	0.522	1.000		
TASKSELF	0.730	0.429	0.410	1.000	
VERBINTL	-0.302	-0.092	-0.436	-0.414	1.000

```
        PSI
           PERFORMN   JOBSATIS

           ________   ________
             0.467      0.522
        THETA EPS
           PERFORMM   JBSATIS1   JBSATIS2

           ________   ________   ________
             0.000      0.378      0.360
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ

           ________   ________   ________   ________   ________
             0.676      0.605      0.414      0.521      0.150
        REGRESSION MATRIX ETA ON KSI (STANDARDIZED)
           AMOTIVAT   TASKSELF   VERBINTL

           ________   ________   ________
PERFORMN      0.000      0.730      0.000
JOBSATIS      0.501      0.333      0.264
Joreskog/Sorbom pp. 155-156 Model ****

MODIFICATION INDICES AND ESTIMATED CHANGE
        MODIFICATION INDICES FOR LAMBDA Y
           PERFORMN   JOBSATIS

           ________   ________
PERFORMM      0.000      1.647
JBSATIS1      0.570      0.000
JBSATIS2      0.570      0.000
        ESTIMATED CHANGE FOR LAMBDA Y
           PERFORMN   JOBSATIS

           ________   ________
PERFORMM      0.000     -0.153
JBSATIS1      0.192      0.000
JBSATIS2     -0.160      0.000
        MODIFICATION INDICES FOR LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL

           ________   ________   ________
ACHIMOT1      0.000      0.009      0.480
ACHIMOT2      0.000      0.169      0.480
TASKSEL1      0.044      0.000      0.000
TASKSEL2      0.030      0.000      3.328
VERBALIQ      0.000      0.704      0.000
        ESTIMATED CHANGE FOR LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL

           ________   ________   ________
ACHIMOT1      0.000     -0.016      0.059
ACHIMOT2      0.000     -0.080     -0.068
TASKSEL1      0.049      0.000      0.001
TASKSEL2     -0.038      0.000      0.109
VERBALIQ      0.000     -1.329      0.000
        MODIFICATION INDICES FOR BETA
           PERFORMN   JOBSATIS

           ________   ________
PERFORMN      0.000      1.647
JOBSATIS      0.000      0.000
        ESTIMATED CHANGE FOR BETA
           PERFORMN   JOBSATIS

           ________   ________
PERFORMN      0.000     -0.153
JOBSATIS      0.000      0.000
        MODIFICATION INDICES FOR GAMMA
           AMOTIVAT   TASKSELF   VERBINTL

           ________   ________   ________
PERFORMN      0.003      0.000      3.068
JOBSATIS      0.000      0.704      0.000
        ESTIMATED CHANGE FOR GAMMA
           AMOTIVAT   TASKSELF   VERBINTL

           ________   ________   ________
PERFORMN     -0.012      0.000     -0.107
JOBSATIS      0.000      0.284      0.000
NO NON-ZERO MODIFICATION INDICES FOR PHI
NO NON-ZERO MODIFICATION INDICES FOR PSI
```

```
MODIFICATION INDICES FOR THETA EPS
   PERFORMM   JBSATIS1   JBSATIS2

    0.704      0.000      0.000
ESTIMATED CHANGE FOR THETA EPS
   PERFORMM   JBSATIS1   JBSATIS2

    1.054      0.000      0.000
MODIFICATION INDICES FOR THETA DELTA
   ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ

    0.000      0.000      0.000      0.000      0.704
ESTIMATED CHANGE FOR THETA DELTA
   ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ

    0.000      0.000      0.000      0.000    -19.467
MAXIMUM MODIFICATION INDEX IS    3.33 FOR ELEMENT ( 4, 3) OF LAMBDA X
 THE PROBLEM USED     8736 BYTES (=   0.3% OF AVAILABLE WORKSPACE)
                  TIME USED :    0.00 SECONDS

08-Jul-98   LISR152a.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156          Page  2
15:44:41    TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

Preceding task required .40 seconds CPU time;  7.99 seconds elapsed.

  30  0
    29 command lines read.
     0 errors detected.
     0 warnings issued.
     1 seconds CPU time.
    13 seconds elapsed time.
       End of job.
```

Appendix C
Maximum-Likelihood Analysis for the Model that Performance Predicts Job Satisfaction
(Reliability of Verbal Intelligence (X_5) Scores Fixed as 1.0)

lisr152b.lst 7/9/98

```
08-Jul-98   SPSS RELEASE 4.1 FOR IBM OS/MVS                                    Page   1
15:45:47    TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

For MVS/ESA/JES3        TEXAS A&M UNIVERSITY: CIS          License Number 1267
This software is functional through August 31, 1998.

   1  0  title 'LISR152b.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156'
   2  0  data list file=abc records=3 table/1 id 1-4
   3  0    /2 /3
This command will read 3 records from 'E100BT.ARTHUR.DAT'
Variable   Rec   Start     End         Format

ID           1       1       4         F4.0

   4  0  lisrel
   5  0    /"Joreskog/Sorbom pp. 155-156 Model ****"
   6  0    /DA NI=8 NO=122 MA=CM
   7  0    /LA
   8  0    /'PERFORMN' 'JBSATIS1' 'JBSATIS2' 'ACHIMOT1'
   9  0    /'ACHIMOT2' 'TASKSEL1' 'TASKSEL2' 'VERBALIQ'
  10  0    /KM SY
  11  0    /(8F8.3)
  12  0    /   4.368
  13  0    /   2.997  11.765
  14  0    /   2.314   6.043   7.896
  15  0    /   0.526   1.351   1.458   3.802
  16  0    /   0.814   2.007   1.204   1.466   4.244
  17  0    /   2.456   2.082   1.967   0.847   0.716   4.666
  18  0    /   2.183   1.590   1.818   0.691   0.738   2.429   4.244
  19  0    /  -2.723  -1.953  -0.390  -1.416  -2.083  -2.318  -1.308  13.323
  20  0    /MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
  21  0    /LE
  22  0    /'PERFORMN' 'JOBSATIS'
  23  0    /LK
  24  0    /'AMOTIVAT' 'TASKSELF' 'VERBINTL'
  25  0    /FR LY(3,2) LX(2,1) LX(4,2) BE(2,1)
  26  0    /FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
  27  0    /VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
  28  0    /OU SE SS SC TV MI ND=3
There are 3,033,680 bytes of memory available.
The largest contiguous area has 3,027,384 bytes.

                LISREL 7:  ESTIMATION OF LINEAR STRUCTURAL EQUATION SYSTEMS
                        PROGRAM VERSION 7.16       DISTRIBUTED BY

                        SCIENTIFIC SOFTWARE, INC.
                        1369 NEITZEL ROAD
                        MOORESVILLE, INDIANA 46158
                        (317) 831-6336


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                        MVS - L I S R E L  7.16
                                BY
                    KARL G JORESKOG AND DAG SORBOM

THE FOLLOWING LISREL CONTROL LINES HAVE BEEN READ :

Joreskog/Sorbom pp. 155-156 Model ****
DA NI=8 NO=122 MA=CM
LA
PERFORMM   JBSATIS1   JBSATIS2   ACHIMOT1
ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
KM SY
(8F8.3)
MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
LE
PERFORMN   JOBSATIS
LK
AMOTIVAT   TASKSELF   VERBINTL
FR LY(3,2) LX(2,1) LX(4,2) BE(2,1)
FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
OU SE SS SC TV MI ND=3
Joreskog/Sorbom pp. 155-156 Model ****
                        NUMBER OF INPUT VARIABLES  8
                        NUMBER OF Y - VARIABLES    3
                        NUMBER OF X - VARIABLES    5
                        NUMBER OF ETA - VARIABLES  2
                        NUMBER OF KSI - VARIABLES  3
                        NUMBER OF OBSERVATIONS   122
Joreskog/Sorbom pp. 155-156 Model ****
        COVARIANCE MATRIX TO BE ANALYZED
           PERFORMM   JBSATIS1   JBSATIS2   ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           --------   --------   --------   --------   --------   --------   --------   --------
PERFORMM      4.368
JBSATIS1      2.997     11.765
JBSATIS2      2.314      6.043      7.896
ACHIMOT1      0.526      1.351      1.458      3.802
ACHIMOT2      0.814      2.007      1.204      1.466      4.244
TASKSEL1      2.456      2.082      1.967      0.847      0.716      4.666
TASKSEL2      2.183      1.590      1.818      0.691      0.738      2.429      4.244
VERBALIQ     -2.723     -1.953     -0.390     -1.416     -2.083     -2.318     -1.308     13.323
Joreskog/Sorbom pp. 155-156 Model ****

PARAMETER SPECIFICATIONS
        LAMBDA Y
           PERFORMN   JOBSATIS
           --------   --------
PERFORMM          0          0
JBSATIS1          0          0
JBSATIS2          0          1
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
ACHIMOT1          0          0          0
ACHIMOT2          2          0          0
TASKSEL1          0          0          0
TASKSEL2          0          3          0
VERBALIQ          0          0          0
        BETA
           PERFORMN   JOBSATIS
           --------   --------
PERFORMN          0          0
JOBSATIS          4          0
        GAMMA
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
```

```
PERFORMN          0          5          0
JOBSATIS          6          0          7
        PHI
           AMOTIVAT   TASKSELF   VERBINTL

AMOTIVAT          8
TASKSELF          9         10
VERBINTL         11         12         13
        PSI
           PERFORMN   JOBSATIS

              14         15
        THETA EPS
           PERFORMN   JBSATIS1   JBSATIS2

               0         16         17
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ

              18         19         20         21          0
Joreskog/Sorbom pp. 155-156 Model ****
INITIAL ESTIMATES (TSLS)
        LAMBDA Y
           PERFORMN   JOBSATIS

PERFORMM      1.000      0.000
JBSATIS1      0.000      1.000
JBSATIS2      0.000      0.797
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL

ACHIMOT1      1.000      0.000      0.000
ACHIMOT2      0.877      0.000      0.000
TASKSEL1      0.000      1.000      0.000
TASKSEL2      0.000      0.939      0.000
VERBALIQ      0.000      0.000      1.000
        BETA
           PERFORMN   JOBSATIS

PERFORMN      0.000      0.000
JOBSATIS      0.688      0.000
        GAMMA
           AMOTIVAT   TASKSELF   VERBINTL

PERFORMN      0.000      0.926      0.000
JOBSATIS      0.954      0.000      0.168
        COVARIANCE MATRIX OF ETA AND KSI
           PERFORMN   JOBSATIS   AMOTIVAT   TASKSELF   VERBINTL

PERFORMN      4.368
JOBSATIS      3.437      8.239
AMOTIVAT      0.759      1.808      1.671
TASKSELF      2.395      2.114      0.820      2.587
VERBINTL     -1.744     -0.711     -1.833     -1.885     13.323
        PSI
           PERFORMN   JOBSATIS

              2.151      4.269
        THETA EPS
           PERFORMM   JBSATIS1   JBSATIS2

              0.000      4.181      3.081
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ

              2.131      2.958      2.079      1.963      0.000
        SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES
           PERFORMM   JBSATIS1   JBSATIS2

              1.000      0.663      0.629
```

```
        SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ

            0.440      0.303      0.554      0.537      1.000
        SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS
           PERFORMN   JOBSATIS

            0.507      0.482
        TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS  IS  0.620
Joreskog/Sorbom pp. 155-156 Model ****

LISREL ESTIMATES (MAXIMUM LIKELIHOOD)
        LAMBDA Y
           PERFORMN   JOBSATIS

PERFORMM    1.000      0.000
JBSATIS1    0.000      1.000
JBSATIS2    0.000      0.834
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL

ACHIMOT1    1.000      0.000      0.000
ACHIMOT2    1.169      0.000      0.000
TASKSEL1    0.000      1.000      0.000
TASKSEL2    0.000      0.861      0.000
VERBALIQ    0.000      0.000      1.000
        BETA
           PERFORMN   JOBSATIS

PERFORMN    0.000      0.000
JOBSATIS    0.583      0.000
        GAMMA
           AMOTIVAT   TASKSELF   VERBINTL

PERFORMN    0.000      0.923      0.000
JOBSATIS    1.179      0.000      0.175
        COVARIANCE MATRIX OF ETA AND KSI
           PERFORMN   JOBSATIS   AMOTIVAT   TASKSELF   VERBINTL

PERFORMN    4.368
JOBSATIS    2.987      7.371
AMOTIVAT    0.689      1.569      1.231
TASKSELF    2.525      1.948      0.747      2.736
VERBINTL   -2.136     -0.833     -1.628     -2.316     13.323
        PSI
           PERFORMN   JOBSATIS

            2.038      3.925
        THETA EPS
           PERFORMM   JBSATIS1   JBSATIS2

            0.000      4.517      2.858
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ

            2.571      2.562      1.930      2.215      0.000
        SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES
           PERFORMM   JBSATIS1   JBSATIS2

            1.000      0.620      0.642
        SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ

            0.324      0.396      0.586      0.478      1.000
        SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS
           PERFORMN   JOBSATIS

            0.533      0.468
        TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS  IS  0.656
W_A_R_N_I_N_G : THETA EPS is not positive definite
```

```
W A R N I N G : THETA DELTA is not positive definite


        CHI-SQUARE WITH  15 DEGREES OF FREEDOM =    14.08 (P = .519)
                  GOODNESS OF FIT INDEX =0.970
             ADJUSTED GOODNESS OF FIT INDEX =0.927
                 ROOT MEAN SQUARE RESIDUAL =     0.284
Joreskog/Sorbom pp. 155-156 Model ****
SUMMARY STATISTICS FOR FITTED RESIDUALS
SMALLEST FITTED RESIDUAL =    -1.120
  MEDIAN FITTED RESIDUAL =     0.000
 LARGEST FITTED RESIDUAL =     0.686
STEMLEAF PLOT
-10|2
 - 8|
 - 6|
 - 4|9
 - 2|22
 - 0|88662099710000000
   0|1113570357
   2|104
   4|2
   6|9
SUMMARY STATISTICS FOR STANDARDIZED RESIDUALS
SMALLEST STANDARDIZED RESIDUAL =    -2.302
  MEDIAN STANDARDIZED RESIDUAL =     0.000
 LARGEST STANDARDIZED RESIDUAL =     1.854
STEMLEAF PLOT
 - 2|31
 - 1|8
 - 1|3322
 - 0|7766
 - 0|22100000000
   0|11234
   0|557789
   1|12
   1|9
Joreskog/Sorbom pp. 155-156 Model ****

STANDARD ERRORS
        LAMBDA Y
           PERFORMN    JOBSATIS

           --------    --------
PERFORMM      0.000       0.000
JBSATIS1      0.000       0.000
JBSATIS2      0.000       0.135
        LAMBDA X
           AMOTIVAT    TASKSELF    VERBINTL

           --------    --------    --------
ACHIMOT1      0.000       0.000       0.000
ACHIMOT2      0.337       0.000       0.000
TASKSEL1      0.000       0.000       0.000
TASKSEL2      0.000       0.138       0.000
VERBALIQ      0.000       0.000       0.000
        BETA
           PERFORMN    JOBSATIS

           --------    --------
PERFORMN      0.000       0.000
JOBSATIS      0.139       0.000
        GAMMA
           AMOTIVAT    TASKSELF    VERBINTL

           --------    --------    --------
PERFORMN      0.000       0.144       0.000
JOBSATIS      0.454       0.000       0.085
        PHI
           AMOTIVAT    TASKSELF    VERBINTL

           --------    --------    --------
AMOTIVAT      0.500
TASKSELF      0.298       0.646
VERBINTL      0.592       0.683       1.713
```

```
        PSI
           PERFORMN   JOBSATIS
           --------   --------
              0.396      1.204
        THETA EPS
           PERFORMM   JBSATIS1   JBSATIS2
           --------   --------   --------
              0.000      1.175      0.799
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           --------   --------   --------   --------   --------
              0.479      0.575      0.424      0.388      0.000
Joreskog/Sorbom pp. 155-156 Model ****

T-VALUES
        LAMBDA Y
           PERFORMN   JOBSATIS
           --------   --------
PERFORMM      0.000      0.000
JBSATIS1      0.000      0.000
JBSATIS2      0.000      6.196
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
ACHIMOT1      0.000      0.000      0.000
ACHIMOT2      3.469      0.000      0.000
TASKSEL1      0.000      0.000      0.000
TASKSEL2      0.000      6.256      0.000
VERBALIQ      0.000      0.000      0.000
        BETA
           PERFORMN   JOBSATIS
           --------   --------
PERFORMN      0.000      0.000
JOBSATIS      4.205      0.000
        GAMMA
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
PERFORMN      0.000      6.399      0.000
JOBSATIS      2.598      0.000      2.056
        PHI
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
AMOTIVAT      2.463
TASKSELF      2.506      4.238
VERBINTL     -2.750     -3.388      7.778
        PSI
           PERFORMN   JOBSATIS
           --------   --------
              5.146      3.259
        THETA EPS
           PERFORMM   JBSATIS1   JBSATIS2
           --------   --------   --------
              0.000      3.844      3.575
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           --------   --------   --------   --------   --------
              5.366      4.454      4.547      5.708      0.000
Joreskog/Sorbom pp. 155-156 Model ****

STANDARDIZED SOLUTION
        LAMBDA Y
           PERFORMN   JOBSATIS
           --------   --------
PERFORMM      2.090      0.000
JBSATIS1      0.000      2.715
JBSATIS2      0.000      2.264
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
ACHIMOT1      1.110      0.000      0.000
```

ACHIMOT2	1.297	0.000	0.000
TASKSEL1	0.000	1.654	0.000
TASKSEL2	0.000	1.425	0.000
VERBALIQ	0.000	0.000	3.650

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.449	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.482	0.000	0.235

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.526	1.000			
AMOTIVAT	0.297	0.521	1.000		
TASKSELF	0.730	0.434	0.407	1.000	
VERBINTL	-0.280	-0.084	-0.402	-0.383	1.000

PSI

PERFORMN	JOBSATIS
0.467	0.532

REGRESSION MATRIX ETA ON KSI (STANDARDIZED)

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.482	0.328	0.235

Joreskog/Sorbom pp. 155-156 Model ****

COMPLETELY STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	0.787
JBSATIS2	0.000	0.801

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.569	0.000	0.000
ACHIMOT2	0.630	0.000	0.000
TASKSEL1	0.000	0.766	0.000
TASKSEL2	0.000	0.691	0.000
VERBALIQ	0.000	0.000	1.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.449	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.482	0.000	0.235

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.526	1.000			
AMOTIVAT	0.297	0.521	1.000		
TASKSELF	0.730	0.434	0.407	1.000	
VERBINTL	-0.280	-0.084	-0.402	-0.383	1.000

PSI

PERFORMN	JOBSATIS
0.467	0.532

```
        THETA EPS
           PERFORMM   JBSATIS1   JBSATIS2
           --------   --------   --------
              0.000      0.380      0.358
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           --------   --------   --------   --------   --------
              0.676      0.604      0.414      0.522      0.000
        REGRESSION MATRIX ETA ON KSI (STANDARDIZED)
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
PERFORMN      0.000      0.730      0.000
JOBSATIS      0.482      0.328      0.235
Joreskog/Sorbom pp. 155-156 Model ****

MODIFICATION INDICES AND ESTIMATED CHANGE
        MODIFICATION INDICES FOR LAMBDA Y
           PERFORMN   JOBSATIS
           --------   --------
PERFORMM      0.000      1.536
JBSATIS1      0.620      0.000
JBSATIS2      0.620      0.000
        ESTIMATED CHANGE FOR LAMBDA Y
           PERFORMN   JOBSATIS
           --------   --------
PERFORMM      0.000     -0.148
JBSATIS1      0.200      0.000
JBSATIS2     -0.167      0.000
        MODIFICATION INDICES FOR LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
ACHIMOT1      0.000      0.005      0.498
ACHIMOT2      0.000      0.147      0.498
TASKSEL1      0.038      0.000      0.000
TASKSEL2      0.032      0.000      3.436
VERBALIQ      0.000      0.591      0.000
        ESTIMATED CHANGE FOR LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
ACHIMOT1      0.000     -0.012      0.050
ACHIMOT2      0.000     -0.075     -0.058
TASKSEL1      0.046      0.000      0.000
TASKSEL2     -0.039      0.000      0.092
VERBALIQ      0.000     -1.465      0.000
        MODIFICATION INDICES FOR BETA
           PERFORMN   JOBSATIS
           --------   --------
PERFORMN      0.000      1.536
JOBSATIS      0.000      0.000
        ESTIMATED CHANGE FOR BETA
           PERFORMN   JOBSATIS
           --------   --------
PERFORMN      0.000     -0.148
JOBSATIS      0.000      0.000
        MODIFICATION INDICES FOR GAMMA
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
PERFORMN      0.001      0.000      3.082
JOBSATIS      0.000      0.591      0.000
        ESTIMATED CHANGE FOR GAMMA
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
PERFORMN     -0.008      0.000     -0.089
JOBSATIS      0.000      0.256      0.000
NO NON-ZERO MODIFICATION INDICES FOR PHI
NO NON-ZERO MODIFICATION INDICES FOR PSI
        MODIFICATION INDICES FOR THETA EPS
           PERFORMM   JBSATIS1   JBSATIS2
           --------   --------   --------
              0.591      0.000      0.000
```

```
        ESTIMATED CHANGE FOR THETA EPS
           PERFORMM    JBSATIS1    JBSATIS2

           ________    ________    ________
              0.971       0.000       0.000
        MODIFICATION INDICES FOR THETA DELTA
           ACHIMOT1    ACHIMOT2    TASKSEL1    TASKSEL2    VERBALIQ

           ________    ________    ________    ________    ________
              0.000       0.000       0.000       0.000       0.592
        ESTIMATED CHANGE FOR THETA DELTA
           ACHIMOT1    ACHIMOT2    TASKSEL1    TASKSEL2    VERBALIQ

           ________    ________    ________    ________    ________
              0.000       0.000       0.000       0.000     -26.192
       MAXIMUM MODIFICATION INDEX IS    3.44 FOR ELEMENT ( 4, 3) OF LAMBDA X
        THE PROBLEM USED     8736 BYTES (=   0.3% OF AVAILABLE WORKSPACE)
                        TIME USED :    0.00 SECONDS
08-Jul-98   LISR152b.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156          Page   2
15:46:05    TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

Preceding task required .41 seconds CPU time;  12.51 seconds elapsed.

  29  0
    28 command lines read.
     0 errors detected.
     0 warnings issued.
     1 seconds CPU time.
    18 seconds elapsed time.
       End of job.
```

Appendix D
Performance and Job Satisfaction *Reciprocally* Predict Each Other

lisr152c.lst 7/9/98

```
08-Jul-98   SPSS RELEASE 4.1 FOR IBM OS/MVS                                    Page   1
16:03:13    TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

For MVS/ESA/JES3        TEXAS A&M UNIVERSITY: CIS          License Number 1267
This software is functional through August 31, 1998.

   1  0  title 'LISR152c.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156'
   2  0  data list file=abc records=3 table/1 id 1-4
   3  0    /2 /3
This command will read 3 records from 'E1008T.ARTHUR.DAT'
Variable   Rec   Start     End         Format

ID           1       1       4         F4.0

   4  0  lisrel
   5  0    /"Joreskog/Sorbom pp. 155-156 Model ****"
   6  0    /DA NI=8 NO=122 MA=CM
   7  0    /LA
   8  0    /'PERFORMM' 'JBSATIS1' 'JBSATIS2' 'ACHIMOT1'
   9  0    /'ACHIMOT2' 'TASKSEL1' 'TASKSEL2' 'VERBALIQ'
  10  0    /KM SY
  11  0    /(8F8.3)
  12  0    /   4.368
  13  0    /   2.997  11.765
  14  0    /   2.314   6.043   7.896
  15  0    /   0.526   1.351   1.458   3.802
  16  0    /   0.814   2.007   1.204   1.466   4.244
  17  0    /   2.456   2.082   1.967   0.847   0.716   4.666
  18  0    /   2.183   1.590   1.818   0.691   0.738   2.429   4.244
  19  0    /  -2.723  -1.953  -0.390  -1.416  -2.083  -2.318  -1.308  13.323
  20  0    /MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
  21  0    /LE
  22  0    /'PERFORMN' 'JOBSATIS'
  23  0    /LK
  24  0    /'AMOTIVAT' 'TASKSELF' 'VERBINTL'
  25  0    /FR LY(3,2) LX(2,1) LX(4,2) BE(2,1) BE(1,2)
  26  0    /FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
  27  0    /VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
  28  0    /VA 1.998 TD(5,5)
  29  0    /OU SE SS SC TV MI ND=3
There are 3,033,048 bytes of memory available.
The largest contiguous area has 3,026,720 bytes.
```

```
                LISREL 7:  ESTIMATION OF LINEAR STRUCTURAL EQUATION SYSTEMS
                        PROGRAM VERSION 7.16       DISTRIBUTED BY

                        SCIENTIFIC SOFTWARE, INC.
                        1369 NEITZEL ROAD
                        MOORESVILLE, INDIANA 46158
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                          MVS - L I S R E L  7.16
                                    BY
                      KARL G JORESKOG AND DAG SORBOM

THE FOLLOWING LISREL CONTROL LINES HAVE BEEN READ :

Joreskog/Sorbom pp. 155-156 Model ****
DA NI=8 NO=122 MA=CM
LA
PERFORMM   JBSATIS1   JBSATIS2   ACHIMOT1
ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
KM SY
(8F8.3)
MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
LE
PERFORMN   JOBSATIS
LK
AMOTIVAT   TASKSELF   VERBINTL
FR LY(3,2) LX(2,1) LX(4,2) BE(2,1) BE(1,2)
FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
VA 1.998 TD(5,5)
OU SE SS SC TV MI ND=3
Joreskog/Sorbom pp. 155-156 Model ****
                         NUMBER OF INPUT VARIABLES  8
                         NUMBER OF Y - VARIABLES    3
                         NUMBER OF X - VARIABLES    5
                         NUMBER OF ETA - VARIABLES  2
                         NUMBER OF KSI - VARIABLES  3
                         NUMBER OF OBSERVATIONS   122
Joreskog/Sorbom pp. 155-156 Model ****
       COVARIANCE MATRIX TO BE ANALYZED
           PERFORMM   JBSATIS1   JBSATIS2   ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           --------   --------   --------   --------   --------   --------   --------   --------
PERFORMM      4.368
JBSATIS1      2.997     11.765
JBSATIS2      2.314      6.043      7.896
ACHIMOT1      0.526      1.351      1.458      3.802
ACHIMOT2      0.814      2.007      1.204      1.466      4.244
TASKSEL1      2.456      2.082      1.967      0.847      0.716      4.666
TASKSEL2      2.183      1.590      1.818      0.691      0.738      2.429      4.244
VERBALIQ     -2.723     -1.953     -0.390     -1.416     -2.083     -2.318     -1.308     13.323
Joreskog/Sorbom pp. 155-156 Model ****

PARAMETER SPECIFICATIONS
       LAMBDA Y
           PERFORMN   JOBSATIS
           --------   --------
PERFORMM          0          0
JBSATIS1          0          0
JBSATIS2          0          1
       LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
ACHIMOT1          0          0          0
ACHIMOT2          2          0          0
TASKSEL1          0          0          0
TASKSEL2          0          3          0
VERBALIQ          0          0          0
       BETA
           PERFORMN   JOBSATIS
           --------   --------
PERFORMN          0          4
JOBSATIS          5          0
       GAMMA
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
```

PERFORMN	0	6	0
JOBSATIS	7	0	8

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	9		
TASKSELF	10	11	
VERBINTL	12	13	14

PSI

PERFORMN	JOBSATIS
15	16

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0	17	18

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
19	20	21	22	0

Joreskog/Sorbom pp. 155-156 Model ****
INITIAL ESTIMATES (TSLS)

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	1.000
JBSATIS2	0.000	0.797

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	1.000	0.000	0.000
ACHIMOT2	0.877	0.000	0.000
TASKSEL1	0.000	1.000	0.000
TASKSEL2	0.000	0.939	0.000
VERBALIQ	0.000	0.000	1.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	-0.176
JOBSATIS	0.707	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	1.070	0.000
JOBSATIS	0.989	0.000	0.208

COVARIANCE MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	4.476				
JOBSATIS	2.691	7.149			
AMOTIVAT	0.581	1.683	1.671		
TASKSELF	2.395	2.114	0.820	2.587	
VERBINTL	-1.877	-0.786	-1.833	-1.885	11.325

PSI

PERFORMN	JOBSATIS
2.687	4.209

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	4.181	3.081

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
2.131	2.958	2.079	1.963	1.998

SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES

PERFORMM	JBSATIS1	JBSATIS2
1.000	0.631	0.596

```
        SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           --------   --------   --------   --------   --------
              0.440      0.303      0.554      0.537      0.850
        TOTAL COEFFICIENT OF DETERMINATION FOR X - VARIABLES IS  0.976
        SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS
           PERFORMN   JOBSATIS
           --------   --------
              0.400      0.411
        TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS  IS  0.543
Joreskog/Sorbom pp. 155-156 Model ****

LISREL ESTIMATES (MAXIMUM LIKELIHOOD)
        LAMBDA Y
           PERFORMN   JOBSATIS
           --------   --------
PERFORMN      1.000      0.000
JBSATIS1      0.000      1.000
JBSATIS2      0.000      0.881
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
ACHIMOT1      1.000      0.000      0.000
ACHIMOT2      1.138      0.000      0.000
TASKSEL1      0.000      1.000      0.000
TASKSEL2      0.000      0.866      0.000
VERBALIQ      0.000      0.000      1.000
        BETA
           PERFORMN   JOBSATIS
           --------   --------
PERFORMN      0.000     -0.220  <==========
JOBSATIS      0.816      0.000
        GAMMA
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
PERFORMN      0.000      1.111      0.000
JOBSATIS      1.057      0.000      0.265
        COVARIANCE MATRIX OF ETA AND KSI
           PERFORMN   JOBSATIS   AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------   --------   --------
PERFORMN      4.358
JOBSATIS      2.793      6.881
AMOTIVAT      0.554      1.386      1.296
TASKSELF      2.512      2.274      0.773      2.711
VERBINTL     -2.339     -0.654     -1.648     -2.235     11.324
        PSI
           PERFORMN   JOBSATIS
           --------   --------
              2.573      3.904
        THETA EPS
           PERFORMN   JBSATIS1   JBSATIS2
           --------   --------   --------
              0.000      4.921      2.578
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           --------   --------   --------   --------   --------
              2.506      2.566      1.955      2.212      1.998
        SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES
           PERFORMN   JBSATIS1   JBSATIS2
           --------   --------   --------
              1.000      0.583      0.675
        SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           --------   --------   --------   --------   --------
              0.341      0.395      0.581      0.479      0.850
        TOTAL COEFFICIENT OF DETERMINATION FOR X - VARIABLES IS  0.974
        SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS
           PERFORMN   JOBSATIS
           --------   --------
              0.410      0.433
```

```
       TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS  IS  0.547
W_A_R_N_I_N_G : THETA EPS is not positive definite


        CHI-SQUARE WITH  14 DEGREES OF FREEDOM =    12.12 (P = .597)
                  GOODNESS OF FIT INDEX =0.974
              ADJUSTED GOODNESS OF FIT INDEX =0.932
                   ROOT MEAN SQUARE RESIDUAL =     0.287
Joreskog/Sorbom pp. 155-156 Model ****
SUMMARY STATISTICS FOR FITTED RESIDUALS
SMALLEST FITTED RESIDUAL =   -1.299
  MEDIAN FITTED RESIDUAL =   -0.004
 LARGEST FITTED RESIDUAL =    0.627
STEMLEAF PLOT
-12|0
-10|
- 8|
- 6|
- 4|
- 2|881
- 0|9965864443322100000
  0|11278889
  2|034
  4|3
  6|3
SUMMARY STATISTICS FOR STANDARDIZED RESIDUALS
SMALLEST STANDARDIZED RESIDUAL =   -2.041
  MEDIAN STANDARDIZED RESIDUAL =   -0.036
 LARGEST STANDARDIZED RESIDUAL =    1.682
STEMLEAF PLOT
- 2|0
- 1|
- 1|440
- 0|9877655
- 0|31111110000
  0|11334
  0|55889
  1|123
  1|7
Joreskog/Sorbom pp. 155-156 Model ****

STANDARD ERRORS
        LAMBDA Y
           PERFORMN   JOBSATIS
           --------   --------
PERFORMM      0.000      0.000
JBSATIS1      0.000      0.000
JBSATIS2      0.000      0.144
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
ACHIMOT1      0.000      0.000      0.000
ACHIMOT2      0.335      0.000      0.000
TASKSEL1      0.000      0.000      0.000
TASKSEL2      0.000      0.137      0.000
VERBALIQ      0.000      0.000      0.000
        BETA
           PERFORMN   JOBSATIS
           --------   --------
PERFORMN      0.000      0.161  <==========
JOBSATIS      0.210      0.000
        GAMMA
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
PERFORMN      0.000      0.222      0.000
JOBSATIS      0.437      0.000      0.105
        PHI
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
AMOTIVAT      0.523
```

```
TASKSELF       0.304       0.640
VERBINTL       0.600       0.678       1.713
        PSI
           PERFORMN    JOBSATIS
           --------    --------
              0.751       1.243
        THETA EPS
           PERFORMM    JBSATIS1    JBSATIS2
           --------    --------    --------
              0.000       1.152       0.817
        THETA DELTA
           ACHIMOT1    ACHIMOT2    TASKSEL1    TASKSEL2    VERBALIQ
           --------    --------    --------    --------    --------
              0.493       0.584       0.419       0.385       0.000
Joreskog/Sorbom pp. 155-156 Model ****

T-VALUES
        LAMBDA Y
           PERFORMN    JOBSATIS
           --------    --------
PERFORMM       0.000       0.000
JBSATIS1       0.000       0.000
JBSATIS2       0.000       6.131
        LAMBDA X
           AMOTIVAT    TASKSELF    VERBINTL
           --------    --------    --------
ACHIMOT1       0.000       0.000       0.000
ACHIMOT2       3.393       0.000       0.000
TASKSEL1       0.000       0.000       0.000
TASKSEL2       0.000       6.323       0.000
VERBALIQ       0.000       0.000       0.000
        BETA
           PERFORMN    JOBSATIS
           --------    --------
PERFORMN       0.000      -1.362  <==========
JOBSATIS       3.887       0.000
        GAMMA
           AMOTIVAT    TASKSELF    VERBINTL
           --------    --------    --------
PERFORMN       0.000       4.998       0.000
JOBSATIS       2.418       0.000       2.522
        PHI
           AMOTIVAT    TASKSELF    VERBINTL
           --------    --------    --------
AMOTIVAT       2.476
TASKSELF       2.545       4.238
VERBINTL      -2.744      -3.295       6.612
        PSI
           PERFORMN    JOBSATIS
           --------    --------
              3.428       3.141
        THETA EPS
           PERFORMM    JBSATIS1    JBSATIS2
           --------    --------    --------
              0.000       4.272       3.154
        THETA DELTA
           ACHIMOT1    ACHIMOT2    TASKSEL1    TASKSEL2    VERBALIQ
           --------    --------    --------    --------    --------
              5.087       4.393       4.664       5.749       0.000
Joreskog/Sorbom pp. 155-156 Model ****

STANDARDIZED SOLUTION
        LAMBDA Y
           PERFORMN    JOBSATIS
           --------    --------
PERFORMM       2.088       0.000
JBSATIS1       0.000       2.623
JBSATIS2       0.000       2.312
        LAMBDA X
           AMOTIVAT    TASKSELF    VERBINTL
```

ACHIMOT1	1.138	0.000	0.000
ACHIMOT2	1.295	0.000	0.000
TASKSEL1	0.000	1.646	0.000
TASKSEL2	0.000	1.425	0.000
VERBALIQ	0.000	0.000	3.365

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	-0.276
JOBSATIS	0.649	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.876	0.000
JOBSATIS	0.459	0.000	0.339

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.510	1.000			
AMOTIVAT	0.233	0.464	1.000		
TASKSELF	0.731	0.527	0.412	1.000	
VERBINTL	-0.333	-0.074	-0.430	-0.403	1.000

PSI

PERFORMN	JOBSATIS
0.590	0.567

REGRESSION MATRIX ETA ON KSI (STANDARDIZED)

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	-0.107	0.743	-0.079
JOBSATIS	0.389	0.482	0.288

Joreskog/Sorbom pp. 155-156 Model ****

COMPLETELY STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMN	1.000	0.000
JBSATIS1	0.000	0.764
JBSATIS2	0.000	0.821

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.584	0.000	0.000
ACHIMOT2	0.629	0.000	0.000
TASKSEL1	0.000	0.762	0.000
TASKSEL2	0.000	0.692	0.000
VERBALIQ	0.000	0.000	0.922

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	-0.276
JOBSATIS	0.649	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.876	0.000
JOBSATIS	0.459	0.000	0.339

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.510	1.000			
AMOTIVAT	0.233	0.464	1.000		
TASKSELF	0.731	0.527	0.412	1.000	
VERBINTL	-0.333	-0.074	-0.430	-0.403	1.000

PSI

PERFORMN	JOBSATIS

```
          0.590     0.567
       THETA EPS
          PERFORMN  JBSATIS1  JBSATIS2

          0.000     0.417     0.325
       THETA DELTA
          ACHIMOT1  ACHIMOT2  TASKSEL1  TASKSEL2  VERBALIQ

          0.659     0.605     0.419     0.521     0.150
       REGRESSION MATRIX ETA ON KSI (STANDARDIZED)
          AMOTIVAT  TASKSELF  VERBINTL

PERFORMN    -0.107     0.743    -0.079
JOBSATIS     0.389     0.482     0.288
Joreskog/Sorbom pp. 155-156 Model ****

MODIFICATION INDICES AND ESTIMATED CHANGE
       MODIFICATION INDICES FOR LAMBDA Y
          PERFORMN  JOBSATIS

PERFORMM     0.000     0.000
JBSATIS1     1.551     0.000
JBSATIS2     1.551     0.000
       ESTIMATED CHANGE FOR LAMBDA Y
          PERFORMN  JOBSATIS

PERFORMM     0.000     0.000
JBSATIS1     0.284     0.000
JBSATIS2    -0.250     0.000
       MODIFICATION INDICES FOR LAMBDA X
          AMOTIVAT  TASKSELF  VERBINTL

ACHIMOT1     0.000     0.023     0.661
ACHIMOT2     0.000     0.000     0.661
TASKSEL1     0.078     0.000     0.066
TASKSEL2     0.308     0.000     2.700
VERBALIQ     0.000     0.263     0.000
       ESTIMATED CHANGE FOR LAMBDA X
          AMOTIVAT  TASKSELF  VERBINTL

ACHIMOT1     0.000     0.027     0.070
ACHIMOT2     0.000     0.003    -0.080
TASKSEL1    -0.066     0.000    -0.017
TASKSEL2    -0.120     0.000     0.098
VERBALIQ     0.000     1.132     0.000
NO NON-ZERO MODIFICATION INDICES FOR BETA
       MODIFICATION INDICES FOR GAMMA
          AMOTIVAT  TASKSELF  VERBINTL

PERFORMN     0.843     0.000     1.845
JOBSATIS     0.000     0.263     0.000
       ESTIMATED CHANGE FOR GAMMA
          AMOTIVAT  TASKSELF  VERBINTL

PERFORMN     0.275     0.000    -0.103
JOBSATIS     0.000    -0.299     0.000
NO NON-ZERO MODIFICATION INDICES FOR PHI
NO NON-ZERO MODIFICATION INDICES FOR PSI
       MODIFICATION INDICES FOR THETA EPS
          PERFORMM  JBSATIS1  JBSATIS2

          0.263     0.000     0.000
       ESTIMATED CHANGE FOR THETA EPS
          PERFORMM  JBSATIS1  JBSATIS2

         -0.850     0.000     0.000
       MODIFICATION INDICES FOR THETA DELTA
          ACHIMOT1  ACHIMOT2  TASKSEL1  TASKSEL2  VERBALIQ
```

```
          0.000      0.000      0.000      0.000      0.263
       ESTIMATED CHANGE FOR THETA DELTA
          ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
          --------   --------   --------   --------   --------
          0.000      0.000      0.000      0.000     17.352
       MAXIMUM MODIFICATION INDEX IS    2.70 FOR ELEMENT ( 4, 3) OF LAMBDA X
        THE PROBLEM USED     8960 BYTES (=   0.3% OF AVAILABLE WORKSPACE)
                          TIME USED :    0.00 SECONDS
08-Jul-98   LISR152c.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156          Page   2
16:03:22    TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

Preceding task required .41 seconds CPU time;  6.65 seconds elapsed.

  30  0
    29 command lines read.
     0 errors detected.
     0 warnings issued.
     1 seconds CPU time.
     8 seconds elapsed time.
       End of job.
```

Appendix E
Job Satisfaction Predicts Performance

lisr152d.lst 7/9/98

```
08-Jul-98   SPSS RELEASE 4.1 FOR IBM OS/MVS                                    Page   1
15:51:04    TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

For MVS/ESA/JES3        TEXAS A&M UNIVERSITY: CIS          License Number 1267
This software is functional through August 31, 1998.

   1  0  title 'LISR152d.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156'
   2  0  data list file=abc records=3 table/1 id 1-4
   3  0    /2 /3
This command will read 3 records from 'E100BT.ARTHUR.DAT'
Variable   Rec   Start     End         Format

ID           1       1       4         F4.0

   4  0  lisrel
   5  0    /"Joreskog/Sorbom pp. 155-156 Model *****"
   6  0    /DA NI=8 NO=122 MA=CM
   7  0    /LA
   8  0    /'PERFORMM' 'JBSATIS1' 'JBSATIS2' 'ACHIMOT1'
   9  0    /'ACHIMOT2' 'TASKSEL1' 'TASKSEL2' 'VERBALIQ'
  10  0    /KM SY
  11  0    /(8F8.3)
  12  0    /   4.368
  13  0    /   2.997  11.765
  14  0    /   2.314   6.043   7.896
  15  0    /   0.526   1.351   1.458   3.802
  16  0    /   0.814   2.007   1.204   1.466   4.244
  17  0    /   2.456   2.082   1.967   0.847   0.716   4.666
  18  0    /   2.183   1.590   1.818   0.691   0.738   2.429   4.244
  19  0    /  -2.723  -1.953  -0.390  -1.416  -2.083  -2.318  -1.308  13.323
  20  0    /MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
  21  0    /LE
  22  0    /'PERFORMN' 'JOBSATIS'
  23  0    /LK
  24  0    /'AMOTIVAT' 'TASKSELF' 'VERBINTL'
  25  0    /FR LY(3,2) LX(2,1) LX(4,2) BE(1,2)
  26  0    /FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
  27  0    /VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
  28  0    /VA 1.998 TD(5,5)
  29  0    /OU SE SS SC TV MI ND=3 AD=OFF
There are 3,033,168 bytes of memory available.
The largest contiguous area has 3,026,840 bytes.

                LISREL 7:  ESTIMATION OF LINEAR STRUCTURAL EQUATION SYSTEMS
                        PROGRAM VERSION 7.16       DISTRIBUTED BY

                        SCIENTIFIC SOFTWARE, INC.
                        1369 NEITZEL ROAD
                        MOORESVILLE, INDIANA 46158
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```

```
                    MVS - L I S R E L  7.16
                              BY
                KARL G JORESKOG AND DAG SORBOM

THE FOLLOWING LISREL CONTROL LINES HAVE BEEN READ :

Joreskog/Sorbom pp. 155-156 Model ****
DA NI=8 NO=122 MA=CM
LA
PERFORMM   JBSATIS1   JBSATIS2   ACHIMOT1
ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
KM SY
(8F8.3)
MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
LE
PERFORMN   JOBSATIS
LK
AMOTIVAT   TASKSELF   VERBINTL
FR LY(3,2) LX(2,1) LX(4,2) BE(1,2)
FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
VA 1.998 TD(5,5)
OU SE SS SC TV MI ND=3 AD=OFF
Joreskog/Sorbom pp. 155-156 Model ****
                        NUMBER OF INPUT VARIABLES  8
                        NUMBER OF Y - VARIABLES    3
                        NUMBER OF X - VARIABLES    5
                        NUMBER OF ETA - VARIABLES  2
                        NUMBER OF KSI - VARIABLES  3
                        NUMBER OF OBSERVATIONS   122
Joreskog/Sorbom pp. 155-156 Model ****
        COVARIANCE MATRIX TO BE ANALYZED
           PERFORMM   JBSATIS1   JBSATIS2   ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           --------   --------   --------   --------   --------   --------   --------   --------
PERFORMM      4.368
JBSATIS1      2.997     11.765
JBSATIS2      2.314      6.043      7.896
ACHIMOT1      0.526      1.351      1.458      3.802
ACHIMOT2      0.814      2.007      1.204      1.466      4.244
TASKSEL1      2.456      2.082      1.967      0.847      0.716      4.666
TASKSEL2      2.183      1.590      1.818      0.691      0.738      2.429      4.244
VERBALIQ     -2.723     -1.953     -0.390     -1.416     -2.083     -2.318     -1.308     13.323
Joreskog/Sorbom pp. 155-156 Model ****

PARAMETER SPECIFICATIONS
        LAMBDA Y
           PERFORMN   JOBSATIS
           --------   --------
PERFORMM          0          0
JBSATIS1          0          0
JBSATIS2          0          1
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
ACHIMOT1          0          0          0
ACHIMOT2          2          0          0
TASKSEL1          0          0          0
TASKSEL2          0          3          0
VERBALIQ          0          0          0
        BETA
           PERFORMN   JOBSATIS
           --------   --------
PERFORMN          0          4
JOBSATIS          0          0
        GAMMA
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
PERFORMN          0          5          0
```

```
JOBSATIS          6          0          7
        PHI
           AMOTIVAT   TASKSELF   VERBINTL
           ________   ________   ________
AMOTIVAT          8
TASKSELF          9         10
VERBINTL         11         12         13
        PSI
           PERFORMN   JOBSATIS
           ________   ________
                 14         15
        THETA EPS
           PERFORMM   JBSATIS1   JBSATIS2
           ________   ________   ________
                  0         16         17
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           ________   ________   ________   ________   ________
                 18         19         20         21          0
Joreskog/Sorbom pp. 155-156 Model ****
INITIAL ESTIMATES (TSLS)
        LAMBDA Y
           PERFORMN   JOBSATIS
           ________   ________
PERFORMM      1.000      0.000
JBSATIS1      0.000      1.000
JBSATIS2      0.000      0.797
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL
           ________   ________   ________
ACHIMOT1      1.000      0.000      0.000
ACHIMOT2      0.877      0.000      0.000
TASKSEL1      0.000      1.000      0.000
TASKSEL2      0.000      0.939      0.000
VERBALIQ      0.000      0.000      1.000
        BETA
           PERFORMN   JOBSATIS
           ________   ________
PERFORMN      0.000     -0.176
JOBSATIS      0.000      0.000
        GAMMA
           AMOTIVAT   TASKSELF   VERBINTL
           ________   ________   ________
PERFORMN      0.000      1.070      0.000
JOBSATIS      1.123      0.000      0.060
        COVARIANCE MATRIX OF ETA AND KSI
           PERFORMN   JOBSATIS   AMOTIVAT   TASKSELF   VERBINTL
           ________   ________   ________   ________   ________
PERFORMN      5.577
JOBSATIS     -0.471      7.584
AMOTIVAT      0.566      1.768      1.671
TASKSELF      2.624      0.809      0.820      2.587
VERBINTL     -1.772     -1.385     -1.833     -1.885     11.325
        PSI
           PERFORMN   JOBSATIS
           ________   ________
              2.687      5.681
        THETA EPS
           PERFORMM   JBSATIS1   JBSATIS2
           ________   ________   ________
              0.000      4.181      3.081
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           ________   ________   ________   ________   ________
              2.131      2.958      2.079      1.963      1.998
        SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES
           PERFORMM   JBSATIS1   JBSATIS2
           ________   ________   ________
              1.000      0.645      0.610
        SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES
```

```
          ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ

            0.440      0.303      0.554      0.537      0.850
       TOTAL COEFFICIENT OF DETERMINATION FOR X - VARIABLES IS  0.976
       SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS
          PERFORMN   JOBSATIS

            0.518      0.251
       TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS  IS  0.637
Joreskog/Sorbom pp. 155-156 Model ****

LISREL ESTIMATES (MAXIMUM LIKELIHOOD)
       LAMBDA Y
          PERFORMN   JOBSATIS

PERFORMM     1.000      0.000
JBSATIS1     0.000      1.000
JBSATIS2     0.000      0.834
       LAMBDA X
          AMOTIVAT   TASKSELF   VERBINTL

ACHIMOT1     1.000      0.000      0.000
ACHIMOT2     1.184      0.000      0.000
TASKSEL1     0.000      1.000      0.000
TASKSEL2     0.000      0.858      0.000
VERBALIQ     0.000      0.000      1.000
       BETA
          PERFORMN   JOBSATIS

PERFORMN     0.000      0.150
JOBSATIS     0.000      0.000
       GAMMA
          AMOTIVAT   TASKSELF   VERBINTL

PERFORMN     0.000      0.801      0.000
JOBSATIS     3.208      0.000      0.348
       COVARIANCE MATRIX OF ETA AND KSI
          PERFORMN   JOBSATIS   AMOTIVAT   TASKSELF   VERBINTL

PERFORMN     4.348
JOBSATIS     2.689      7.290
AMOTIVAT     0.938      1.611      0.679
TASKSELF     2.506      1.991      0.870      2.755
VERBINTL    -2.033     -1.289     -1.629     -2.296     11.327
       PSI
          PERFORMN   JOBSATIS

            1.937      2.569
       THETA EPS
          PERFORMM   JBSATIS1   JBSATIS2

            0.000      4.475      2.822
       THETA DELTA
          ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ

            3.123      3.293      1.911      2.214      1.998
       SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES
          PERFORMM   JBSATIS1   JBSATIS2

            1.000      0.620      0.643
       SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES
          ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ

            0.179      0.224      0.590      0.478      0.850
       TOTAL COEFFICIENT OF DETERMINATION FOR X - VARIABLES IS  0.961
       SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS
          PERFORMN   JOBSATIS

            0.554      0.648
       TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS  IS  0.797
```

```
W_A_R_N_I_N_G : THETA EPS is not positive definite


        CHI-SQUARE WITH  15 DEGREES OF FREEDOM =    23.34 (P = .077)
                    GOODNESS OF FIT INDEX =0.953
            ADJUSTED GOODNESS OF FIT INDEX =0.886
                ROOT MEAN SQUARE RESIDUAL =     0.304
Joreskog/Sorbom pp. 155-156 Model ****
SUMMARY STATISTICS FOR FITTED RESIDUALS
SMALLEST FITTED RESIDUAL =   -0.690
  MEDIAN FITTED RESIDUAL =    0.000
 LARGEST FITTED RESIDUAL =    0.686
STEMLEAF PLOT
- 6|96
- 4|1
- 2|9106
- 0|552654220000000
  0|2367901
  2|1119
  4|
  6|669
SUMMARY STATISTICS FOR STANDARDIZED RESIDUALS
SMALLEST STANDARDIZED RESIDUAL =   -2.781
  MEDIAN STANDARDIZED RESIDUAL =    0.000
 LARGEST STANDARDIZED RESIDUAL =    2.784
STEMLEAF PLOT
- 2|821
- 1|75332
- 0|98653211000000
  0|334466
  1|223889
  2|88
LARGEST NEGATIVE STANDARDIZED RESIDUALS
RESIDUAL FOR VERBALIQ AND VERBALIQ =  -2.781
LARGEST POSITIVE STANDARDIZED RESIDUALS
RESIDUAL FOR PERFORMM AND PERFORMM =   2.784
RESIDUAL FOR ACHIMOT2 AND ACHIMOT1 =   2.784
Joreskog/Sorbom pp. 155-156 Model ****

STANDARD ERRORS
        LAMBDA Y
           PERFORMN   JOBSATIS

           --------   --------
PERFORMM      0.000      0.000
JBSATIS1      0.000      0.000
JBSATIS2      0.000      0.145
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL

           --------   --------   --------
ACHIMOT1      0.000      0.000      0.000
ACHIMOT2      0.369      0.000      0.000
TASKSEL1      0.000      0.000      0.000
TASKSEL2      0.000      0.137      0.000
VERBALIQ      0.000      0.000      0.000
        BETA
           PERFORMN   JOBSATIS

           --------   --------
PERFORMN      0.000      0.078
JOBSATIS      0.000      0.000
        GAMMA
           AMOTIVAT   TASKSELF   VERBINTL

           --------   --------   --------
PERFORMN      0.000      0.154      0.000
JOBSATIS      1.328      0.000      0.221
        PHI
           AMOTIVAT   TASKSELF   VERBINTL

           --------   --------   --------
AMOTIVAT      0.339
TASKSELF      0.298      0.649
VERBINTL      0.573      0.687      1.713
```

```
        PSI
           PERFORMN   JOBSATIS
           --------   --------
             0.354      1.887
        THETA EPS
           PERFORMM   JBSATIS1   JBSATIS2
           --------   --------   --------
             0.000      1.257      0.858
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           --------   --------   --------   --------   --------
             0.445      0.491      0.427      0.388      0.000
Joreskog/Sorbom pp. 155-156 Model ****

T-VALUES
        LAMBDA Y
           PERFORMN   JOBSATIS
           --------   --------
PERFORMM      0.000      0.000
JBSATIS1      0.000      0.000
JBSATIS2      0.000      5.741
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
ACHIMOT1      0.000      0.000      0.000
ACHIMOT2      3.207      0.000      0.000
TASKSEL1      0.000      0.000      0.000
TASKSEL2      0.000      6.261      0.000
VERBALIQ      0.000      0.000      0.000
        BETA
           PERFORMN   JOBSATIS
           --------   --------
PERFORMN      0.000      1.928
JOBSATIS      0.000      0.000
        GAMMA
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
PERFORMN      0.000      5.211      0.000
JOBSATIS      2.416      0.000      1.574
        PHI
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
AMOTIVAT      2.004
TASKSELF      2.915      4.245
VERBINTL     -2.844     -3.342      6.612
        PSI
           PERFORMN   JOBSATIS
           --------   --------
             5.471      1.361
        THETA EPS
           PERFORMM   JBSATIS1   JBSATIS2
           --------   --------   --------
             0.000      3.561      3.289
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
           --------   --------   --------   --------   --------
             7.014      6.700      4.479      5.706      0.000
Joreskog/Sorbom pp. 155-156 Model ****

STANDARDIZED SOLUTION
        LAMBDA Y
           PERFORMN   JOBSATIS
           --------   --------
PERFORMM      2.085      0.000
JBSATIS1      0.000      2.700
JBSATIS2      0.000      2.253
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL
           --------   --------   --------
ACHIMOT1      0.824      0.000      0.000
```

ACHIMOT2	0.975	0.000	0.000
TASKSEL1	0.000	1.660	0.000
TASKSEL2	0.000	1.425	0.000
VERBALIQ	0.000	0.000	3.365

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.194
JOBSATIS	0.000	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.638	0.000
JOBSATIS	0.979	0.000	0.433

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.478	1.000			
AMOTIVAT	0.546	0.724	1.000		
TASKSELF	0.724	0.444	0.636	1.000	
VERBINTL	-0.290	-0.142	-0.588	-0.411	1.000

PSI

PERFORMN	JOBSATIS
0.446	0.352

REGRESSION MATRIX ETA ON KSI (STANDARDIZED)

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.190	0.638	0.084
JOBSATIS	0.979	0.000	0.433

Joreskog/Sorbom pp. 155-156 Model ****

COMPLETELY STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	0.787
JBSATIS2	0.000	0.802

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.423	0.000	0.000
ACHIMOT2	0.473	0.000	0.000
TASKSEL1	0.000	0.768	0.000
TASKSEL2	0.000	0.692	0.000
VERBALIQ	0.000	0.000	0.922

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.194
JOBSATIS	0.000	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.638	0.000
JOBSATIS	0.979	0.000	0.433

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.478	1.000			
AMOTIVAT	0.546	0.724	1.000		
TASKSELF	0.724	0.444	0.636	1.000	
VERBINTL	-0.290	-0.142	-0.588	-0.411	1.000

PSI

PERFORMN	JOBSATIS
0.446	0.352

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        THETA EPS
           PERFORMM   JBSATIS1   JBSATIS2

             0.000      0.380      0.357
        THETA DELTA
           ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ

             0.821      0.776      0.410      0.522      0.150
        REGRESSION MATRIX ETA ON KSI (STANDARDIZED)
           AMOTIVAT   TASKSELF   VERBINTL

PERFORMN     0.190      0.638      0.084
JOBSATIS     0.979      0.000      0.433
Joreskog/Sorbom pp. 155-156 Model ****

MODIFICATION INDICES AND ESTIMATED CHANGE
        MODIFICATION INDICES FOR LAMBDA Y
           PERFORMN   JOBSATIS

PERFORMM     0.000      0.000
JBSATIS1     2.282      0.000
JBSATIS2     0.017      0.000
        ESTIMATED CHANGE FOR LAMBDA Y
           PERFORMN   JOBSATIS

PERFORMM     0.000      0.000
JBSATIS1     0.348      0.000
JBSATIS2     0.025      0.000
        MODIFICATION INDICES FOR LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL

ACHIMOT1     0.000      0.861      0.308
ACHIMOT2     0.000      2.674      0.308
TASKSEL1     0.023      0.000      0.000
TASKSEL2     0.805      0.000      3.376
VERBALIQ     0.000      7.752      0.000
        ESTIMATED CHANGE FOR LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL

ACHIMOT1     0.000     -0.196      0.052
ACHIMOT2     0.000     -0.394     -0.062
TASKSEL1     0.073      0.000      0.001
TASKSEL2    -0.376      0.000      0.111
VERBALIQ     0.000     -5.752      0.000
        MODIFICATION INDICES FOR BETA
           PERFORMN   JOBSATIS

PERFORMN     0.000      0.000
JOBSATIS     9.411      0.000
        ESTIMATED CHANGE FOR BETA
           PERFORMN   JOBSATIS

PERFORMN     0.000      0.000
JOBSATIS     1.321      0.000
        MODIFICATION INDICES FOR GAMMA
           AMOTIVAT   TASKSELF   VERBINTL

PERFORMN     0.973      0.000      3.641
JOBSATIS     0.000      7.752      0.000
        ESTIMATED CHANGE FOR GAMMA
           AMOTIVAT   TASKSELF   VERBINTL

PERFORMN     0.513      0.000     -0.111
JOBSATIS     0.000      2.000      0.000
NO NON-ZERO MODIFICATION INDICES FOR PHI
NO NON-ZERO MODIFICATION INDICES FOR PSI
NO NON-ZERO MODIFICATION INDICES FOR THETA EPS
NO NON-ZERO MODIFICATION INDICES FOR THETA DELTA
      MAXIMUM MODIFICATION INDEX IS    9.41 FOR ELEMENT ( 2, 1) OF BETA
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